OPERATIONALIZING FREQUENT EMERGENCY DEPARTMENT USE: A SYSTEMIC PERSPECTIVE

By

Jessica M. Goodman

March, 2019

Director of Dissertation: Angela L. Lamson

Major Department: Human Development and Family Science

Frequent emergency department (ED) use has been the topic of much conversation, research, and debate in recent years as the healthcare sector in the U.S. makes the transition from volume- to value-based care. Although there are systemic factors associated with frequent ED use, this phenomenon is operationalized in research and media solely by the number of visits a patient makes to the ED. This linear, unidimensional way of framing the problem leads to interventions and policies that focus on reducing the number of ED visits, while ignoring value-based measures of care such as health outcomes or whether patients are receiving appropriate kinds of care. This dissertation includes six chapters, comprising (a) an introduction to the dissertation, (b) a literature review examining the way in which frequent ED use is defined, and informs research, interventions, media, and policy, (c) a systematic review of research that defines frequent ED use, (d) a chapter outlining the methodology for the empirical research study, (e) an empirical research study using machine learning algorithms to develop ED patient cohorts or clusters based on systemic data, and finally (f) a policy brief in which recommendations are made based on the empirical findings of the original research from this dissertation.

OPERATIONALIZING FREQUENT EMERGENCY DEPARTMENT USE: A SYSTEMIC PERSPECTIVE

A Dissertation Presented to

The Faculty of the Department of Human Development & Family Science

East Carolina University

In Partial Fulfillment of the Requirements for the Degree

Doctor of Philosophy in Medical Family Therapy

by

Jessica M. Goodman

March, 2019

©Jessica M. Goodman, 2019

OPERATIONALIZING FREQUENT EMERGENCY DEPARTMENT USE:

A SYSTEMIC PERSPECTIVE

by

Jessica M. Goodman

APPROVED BY:

DIRECTOR OF
DISSERTATION: _____
Angela L. Lamson, PhD

COMMITTEE MEMBER: _____
Theodore Delbridge, MD

COMMITTEE MEMBER: _____
Ray Hylock, PhD

COMMITTEE MEMBER: _____
Jake Jensen, PhD

CHAIR OF THE DEPARTMENT OF HUMAN DEVELOPMENT & FAMILY SCIENCE:

_____
Sharon Ballard, PhD

DEAN OF THE GRADUATE SCHOOL: _____
Paul Gemperline, PhD

DEDICATION

For my husband. Whether across the ocean or across the hall, you have been my rock, ally, and greatest supporter. I am in awe of, and deeply grateful for your steadfast commitment to do whatever it takes to help me reach my goals. “We’ll figure it out,” has been your mantra as I have pursued my graduate education. This stance and the sacrifices that have come with it have seen us through the challenges of this experience, and so many more. You have also been nurturer and supporter to Genevieve and me through the long days, and late nights. You are an amazing partner, father, and co-parent. Thank you for loving me as I am and reminding me of all I can be. I love you.

To my daughter. You come from a long line of strong women. If I can teach you one thing it is to be who you are, because who you are is truly amazing. In *Daughter of the Forest* (1999), author Juliet Marillier captures what I wish to express:

> You are the blood in my veins, and the beating of my heart. You are my first waking thought, and my last sigh before sleeping. You are - you are bone of my bone, and breath of my breath.

I love you.

To Oliver. You put a lot of long days and late nights in underneath the table, keeping my feet warm. Thank you for your reassuring presence, patience, and kisses. I love you. Woof!

ACKNOWLEDGEMENTS

As a systemic, relational thinker I want to acknowledge those that have supported me in the completion of this dissertation and in earning a PhD. Mom, without you I would not have been able to finish this dissertation or the requirements for the PhD. You showed up, moved in, and got down to the work of being a mother and a "Mimi"–keeping us all not only alive but thriving, without hesitation or complaint. You fiercely and bravely cared for Genevieve when I could not and kept watch over me too. Long before that, you cultivated my gifts in writing and communication. I have always admired your love of knowledge, commitment to learning, and curiosity about the world. Without your example, this moment would not be possible.

Angela, I came to you with a vision, and you said, "Yes!" with an enthusiasm matched only by my own. You have always believed in me. You have recognized my strengths and my potential. You have supported and challenged me to do my best work. You have pushed through challenges with unshakable confidence and a steadiness that in turn steadied me. You have given me a map but encouraged me to find my own path. Finally, you have cared for not just me, but my family. I have learned so much from you, and I also know that the learning has just started.

Ray, thank you for navigating the new and uncharted waters of interdisciplinary collaboration between Medical Family Therapy and Health Informatics with me. You gave of your time, talent, and self with patience and care. You shouldered great responsibility without complaint. I have learned a vast amount from our work together over the past nearly two years.

To my committee, thank you for your support, feedback, and thoughtfulness. I am grateful to have mentors that take such care with my learning and development as a professional. You have also been examples to me of how to support others through the journey I have been on, when I find myself in the role of mentor or committee member.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 3

CHAPTER 5

LIST OF FIGURES

PREFACE

As a child, when people asked me what I wanted to do when I grew up, I would reply that I did not know; but whatever I did, I wanted to be on the cutting edge, creating new ideas and contributing to the expansion of a field. At the same time, the values of social justice and equity, learned through education and experiences in my community, shaped my path, and helped set the course for a career of helping others. It was not until I was working as an emergency services clinician in emergency departments in Boston, that I understood what I would do to work toward both creating something new and supporting social justice. It was through my experience as a clinician in the emergency department that I learned first-hand the value of collaboration among providers and across systems in a healthcare setting. I observed that when providers from different disciplines collaborated to treat patients, the outcomes improved. With greater collaboration, the voices of patients were more likely to be a part of treatment decisions and thus patients seemed to have more agency in their care.

It was in this context that I reached out to Dr. Angela Lamson to inquire about the program at ECU in Medical Family Therapy (MedFT). I had learned about MedFT only months before, and yet I felt sure that I had found my calling. As I read and re-read the issue of *Family Therapy Magazine* (Gawinski & Rosenberg, 2015) that focused on MedFT, and journal articles I found online, I knew this was my way to contribute. Talking to Dr. Lamson, and learning more about the program, I became confident that earning a PhD in MedFT and working from a biopsychosocial-spiritual (Engel, 1977, 1980; Wright, Watson, & Bell, 1996) and systemic (vonBertalanffy, 1968) perspective to support individuals and systems around whole health through research, policy, and clinical work was the right fit. Moreover, I knew that my work

focused on the ED would meet both my childhood goals of creating new ideas and expanding the field, while working for social justice and health equity.

I began searching the literature on frequent ED use in the first year of the MedFT PhD program and learned that the way this construct is operationalized leads to conceptualization and treatment of the phenomenon from a linear, unidimensional, framework—number of ED visits over a set period of time. This ignores systemic factors associated with use and the unique needs of patients that may be sicker and more vulnerable than other patients, for example.

My belief is that as the result of this research, we might be closer to a systemic understanding of ED use that takes into account the many factors associated with use. Because the way we define ED use seems to influence the interventions and policies that are created to address it. I hope that future researchers will take into account this more systemic view. Likewise, as our country moves to value-based care, I hope the contents of this dissertation provide a strong argument for looking at outcomes based not just on cost or resource use, but also value. Value-based assessments would include health outcomes and whether patients have access to the appropriate types of care (including the ED). In subsequent work, we plan to determine whether we can predict ED use based on the patient cohorts created herein, and use that information to inform tailored, empirically-based interventions to provide value-based care. The findings of this dissertation have implications for MedFTs at both macro- and microsystemic levels. At the macrosystemic level, MedFTs can contribute a systemic lens to research, policies, and practice. Through MedFT training, I am confident in engaging multiple systems simultaneously from the patient system to provider systems and including administrative and financial billing systems. As systems thinkers we intervene with larger systems (Imber-Black, 1988) via research, clinical practice, and policy-levels to support interdisciplinary collaboration.

At the microsystemic level, MedFTs can hold multiple systemic factors associated with ED patient use in mind as they construct case conceptualizations as well as engage in collaboration and treatment planning with other clinicians.

REFERENCES

Gawinski, B. & Rosenberg, T. (2015). Beginning a career in medical family therapy. *Family Therapy Magazine, 14*(1): 36-39.

Imber-Black, E. (1988). *Families and larger systems: A family therapist's guide through the labyrinth*. New York: Guilford Press.

CHAPTER 1: INTRODUCTION

Although emergency medical care was documented as early as the 1800s, emergency medicine as a field only dates back fifty years to the 1960's (Suter, 2012). Dominique Jean Larrey, Napoleon's chief surgeon is credited with developing the concept of triage and a horse drawn "ambulance" to gather the injured after noticing the lack of immediate care available to soldiers injured in battle (Nakao, Ukai, & Kotani, 2017). In the same era, general practice physicians were most commonly charged with attending to emergencies by way of making house calls to their patients around the clock. In World War II, doctors had learned trauma procedures to care for patients on the field (Goniewicz, 2013). At that time, it became apparent that treatment in the hospital would be more beneficial than a private office, leading to the creation of emergency departments (EDs) (Suter, 2012). However, early emergency departments were small, and run by a rotating shift of physicians, ranging from interns in their first year to on-call physicians from varying specialties including psychiatry and dermatology. These physicians were skilled at handling cases that were in their specialty but delays in patient care and misdiagnoses occurred with some frequency when faced with emergencies outside their specialty.

It was not until the 1960s that two groups, one in Alexandria, VA and the other in Pontiac, MI, separately recognized the need for an emergency medicine specialization and became the first organized physicians to specialize in providing medical care in an ED setting (Suter, 2012). A report published in 1966 by the National Academy of Sciences documenting the lack of care in the ED as well as increasing awareness of the disparity between the trauma care received by soldiers in the field during the Vietnam War and what was available to citizens in the U.S. healthcare system, highlighted the need for improved ED care, which further propelled the

development of ED medicine (NAS, 1966). During the 1970s, resident training in emergency medicine was established, and recognition of this area of expertise as a specialty in medicine was recognized by the American Medical Association, and later by the American Board of Emergency Medicine (Suter, 2012). The 1990s saw emergency medicine continue to grow, in part fueled by popular media portrayals from movies and television shows such as "ER." In fact, Suter (2012) argues that media portrayals have been a major factor in promoting the value of and demand for emergency medicine. This, in combination with the advancement of medical technology, rapid urbanization, increased need for trauma care, the success of emergency medicine in other countries, and other factors, advanced the need for emergency medicine in the U.S., and has improved the medical system overall.

In recent times there has been an increasing demand for emergency services in the U.S. (IOM, 2006). According to the Centers for Disease Control (CDC) (2014), there are 141.1 million visits to the ED each year, equaling 45.1 visits to the ED per one-hundred persons. This is up from 90.3 million, or 34.2 visits per one-hundred persons, in 1996. In fact, the annual frequency of U.S. ED visits is increasing at a rate faster than population growth (Tang, Stein, Hsia, Maselli, & Gonzales, 2010). For example, while the population grew by fifteen percent from 1997 to 2007, the number of annual ED visits increased by 43 percent—almost a three-fold increase (National Center for Health Statistics, 2009). Patient and clinician preferences as well as legal concerns are some of the rationales posited for the increase per capita in ED visits (Casalino, 2010; Pitts, Carrier, Rich, & Kellermann, 2010; Schuur & Venkatesh, 2012). As a result of the increasing number of annual ED visits, overcrowding has become a concern. This led the Institute of Medicine (IOM) to describe the state of emergency care in the U.S. as, "at the breaking point" (IOM, 2006).

Frequent ED use has most commonly been operationalized as number of visits per year (Goodman et al., 2018). The original goal of creating such definitions was to address the issue of overcrowding in the ED, by focusing on reducing the number of visits made by a given patient (Cook et al., 2004; Hunt et al., 2006; Naughton et al., 2010; Sun, Burstin, & Brennan, 2003). However, the bulk of research that employs such definitions of frequent ED use lack empirical basis or theoretical foundation.

Frequent users have been found to have differing characteristics across studies. For example, some studies have found that the frequent ED user population is more likely to have mental health and substance abuse problems, while others have determined that physical diseases, such as chronic conditions, are more prevalent (Doupe et al., 2012; Huang, Tsai, Chen, Hu, & Yang, 2003; Hunt, Weber, Showstack, Colby, & Callaham, 2006; Mandelberg, Kuhn, & Kohn, 2000; Moore, Gerdtz, Manias, Hepworth, & Dent, 2007; Sun, Burstin, & Brennan, 2003). Predictive characteristics of frequent ED use have also varied widely, ranging from things such as demographics to type of insurance, and health conditions (Krieg, Hudon, Chouinard, & Dufour, 2016). For example, some studies have found that men are more likely to be frequent users while others have found the reverse, with women attending the ED more frequently (Doupe et al., 2012; Palmer, Leblanc-Duchin, Murray, & Atkinson, 2014).

While popular opinion and media portrayals tend to cast frequent ED users as uninsured or too lazy to seek primary care, for example, studies have found that this population tends to be sicker and require more healthcare services overall (i.e., care beyond the ED). In fact, this population has been found to have complex medical and social needs, such as chronic physical and mental health conditions or homelessness (Chan & Ovens, 2002; Hansagi, Olsson, Sjoberg, Tomson, & Goransson, 2001; Hunt, Weber, Showstack, Colby, & Callaham, 2006; LaCalle &

Rabin, 2010; Moore, Gerdtz, Manias, Hepworth, & Dent, 2007). Frequent ED users actually have greater healthcare utilization across the continuum of care (e.g. from primary through specialty care) than other ED users (Byrne, 2003; Chan & Ovens, 2002; Fuda & Immekus, 2006; Hansagi et al., 2001; Hunt, Weber, Showstack, Colby, & Callaham, 2006; Weber, 2012; Zuckerman & Shen, 2004). Yet, the way in which frequent ED use is defined informs research design, types of interventions, and healthcare policies. For example, Congressional representatives Chris Collins (R-NY) and Bill Flores (R-TX) have introduced a bill to amend the Social Security Act aimed at reducing unnecessary ED visits made by Medicaid enrollees by imposing higher cost sharing for these individuals when they make ED visits that are deemed to be nonemergency in nature (House of Representatives Bill 1323, 2017).

Without a better understanding and systemic definition of frequent ED use—one that is grounded in theory and supported by empirical data—assumptions are made about utilization. The current definitions of frequent ED use and the actions taken in relation to presumed frequent ED utilization (based on number of visits alone), could be detrimental to patient care and outcomes. If this population is indeed sicker, then how do we know that a one-size-fits-all goal, such as reducing the number of ED visits made by these individuals, is appropriate? It is possible that by focusing on and incentivizing a reduction in the number of visits without understanding the systemic needs of patients, people will not receive the care they need, and become sicker or die needlessly.

Systems Theory

In order to better explore these unique experiences, a theory was needed to capture the complex and systemic factors that influence the phenomenon of frequent ED use. As such, general systems theory was used as the foundation for this dissertation (vonBertalanffy, 1968).

Below is a description of the advantages of incorporating this theory into this dissertation, including a brief comparison to a more limiting framework, The Andersen model (Andersen, 1995). While further comparison of the value added by general systems theory as opposed to other theories could have been provided, this is not the purpose of this dissertation. Rather, the point of incorporating this theory is to help better understand the phenomenon of ED use. General systems theory (vonBertalanffy, 1968) was selected because it emphasizes the need to understand the context in which an event or behavior is occurring in order to make sense of the phenomenon. Specifically, systems theory posits that a system cannot be understood by only studying components individually, but rather should be explored and analyzed via the interactions of its components and the nonlinearity of said interactions. In the context of defining frequent utilization of the ED, utilization should not be reduced to individual factors (e.g., characteristics of use or a social location of the patient population), but instead must consider how these individual components interact to reflect a holistic view of what comprises and influences ED use. This does not negate the importance of individual components but suggests they should not be used in isolation to form the definition for frequent utilization.

As mentioned above, general systems theory is not the only framework that exists to understand the phenomenon of frequent ED use. The Andersen model posits that an individual's use of health services is a function of their predisposition to seek care (e.g., demographic characteristics, social structure, beliefs), factors that affect access to care (e.g., availability of health insurance that would enable or impede use), and underlying clinical needs (e.g., chronic medical conditions, mental health, cognitive function) that precipitate an encounter with the health care system (Andersen, 1995). While the Andersen Model originally focused on the family system as the unit of analysis, Andersen states that he later (no known attributable date)

shifted to the individual as the unit of analysis due to the challenges related to developing a measure at the family level. Given the fact that this model takes into account systems, but measures only at the intra-individual level, it is therefore inadequate for assessing ED utilization from a multidimensional, systemic perspective. A more robust, yet systemic option is needed to identify and analyze frequent ED use.

Purpose and Design

For the purpose of this dissertation, general systems theory was employed to better understand the many systemic levels associated with emergency department use, and to define ED patient subgroups. While researchers have published literature operationalizing the phenomenon of frequent ED use, these works have ubiquitously focused on number of visits, in a linear, unidimensional fashion, and lack empirical and theoretical grounding. This has resulted in research, practice, and policy that examines both the phenomenon and patients through the lens of whether they have visited "too many" times or measured outcomes based on the goal of reducing the number of visits rather than examining whether use was appropriate, patients received appropriate kinds of care, or their service needs were met, for example. As such, the purpose of this research is to gain an understanding of the systemic factors that contribute to ED use and develop understanding of the unique patient groups that utilize the ED.

This dissertation evolves from a literature review (Chapter 2) exploring how the definition of frequent ED use informs research design, types of interventions, popular media portrayals, and healthcare policies. Then, a systematic review (Chapter 3) is offered as a way to identify how frequent ED use is operationalized and justified in the literature. Based on the results of the systematic review, the design for an empirical research study is offered in Chapter 4. The structural basis of the study (i.e. data, machine learning algorithms, etc.) is provided.

Specifically, numerous machine learning algorithms are described, and the process by which these will be employed to identify "clusters" or subgroups of ED users are explored.

More specifically, Chapter 2 offers a review of research, media reports, and policies addressing how frequent ED use is portrayed and defined. This chapter is organized into sections based on these four sources: (a) research that defines frequent use (e.g. peer-reviewed literature focused on how frequent ED use is defined, characteristics of these users); (b) research on interventions to address frequent use; (c) media (e.g. newspaper articles explaining the "problem" of frequent ED use and interventions used to address it); (d) policy (e.g. policy briefs and state bills and legislation attempting to describe frequent ED use, and propose policies intended to address frequent ED use).

Then, a systematic review is presented in Chapter 3. The systematic review was grounded in systems theory and conducted to address the question: "How is frequent ED use operationalized?" After a systematic review of three databases, 162 articles met full text criteria for inclusion. In analyzing the 162 articles, three clusters emerged based on the study populations addressed in the articles (a) a general category (which included all patients and diagnoses); (b) target populations (for articles that focused on a specific population); (c) target diagnosis (for articles that focused on a specific diagnosis).

Findings were focused on the definition of frequent ED use and the justifications given by the articles' authors for the definition they selected. The definitions and justifications from all qualifying articles were extracted and analyzed. Research, practice, and policy implications were discussed, and future research directions were recommended in order to offer future research agendas that can more fully represent the complexity of frequent ED use.

Based on the results from Chapter 3, the methodology for an empirical study was constructed. The methodology for this study is presented in Chapter 4. The design for the study was described, including state-level emergency department datasets from Florida and methods using unsupervised machine-learning algorithms in order to identify unique patient "clusters" or subgroups of ED users. A rich description of how the machine learning algorithms assist in analyzing big data are also presented in this chapter.

Chapter 5 is a publishable manuscript that includes the results from the study outlined in Chapter 4. In this chapter, machine learning clustering algorithms were employed to develop patient cohorts based on multiple, comprehensive, state-level databases. We tested the following specific hypotheses: (a) clustering with feature selection produces better fitting clusters than clustering based on number of visits to the ED, (b) feature selection to identify patient characteristics produces better fitting clusters than using select patient characteristics based on the frequent ED user literature and number of visits, (c) using feature selection, patients that visit the ED across multiple, consecutive years will be clustered into different cohorts than those that only visit the ED during a single year, with no use in the following year. A discussion of significant contributions, limitations, and research and policy implications are included.

Chapter 6 of this dissertation is a policy brief that presents policy implications and recommendations based on the results of the empirical study. This chapter suggests that policies addressing the financial and resource constraints related to ED reimbursement and care should address systemic health considerations and outcomes rather than the unidimensional, linear goal of reducing number of visits.

Summary

Although there are exceptions to this, as noted in Chapter 3, this dissertation demonstrates the extent to which the bulk of research and policy focused on frequent ED utilizers lacks an empirical foundation. This finding begs the question, "how are we to know that a change in number of ED visits demonstrates progress or improvement for patients?" This supports the development of an empirical understanding of ED utilization that takes into account systemic factors associated with use. As has been demonstrated, ED users are a heterogeneous group with differing biopsychosocial needs that touch on multiple systemic layers of health and wellbeing. It is critical that future research, clinical interventions, and policy address ED use from a systemic perspective in order to provide appropriate care to patients, and use resources effectively, in order to support the best outcomes.

REFERENCES

Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter? *Journal of Health and Social Behavior, 36*(1), 1-10.

Byrne, M., Murphy, A. W., Plunkett, P. K., McGee, H. M., Murray, A., & Bury, G. (2003). Frequent attenders to an emergency department: A study of primary health care use, medical profile, and psychosocial characteristics. *Annals of Emergency Medicine, 41*, 309-318. doi:10.1067/mem.2003.68

Casalino, L.P. (2010). A Martian's prescription for primary care: Overhaul the physician's workday. *Health Affairs, 29*, 785-90. doi: 10.1377/hlthaff.2010.0133

Centers for Disease Control. (2014). *National hospital ambulatory medical care survey: 2014 emergency department summary tables*. Retrieved from https://www.cdc.gov/nchs/data/nhamcs/web_tables/2014_ed_web_tables.pdf

Chan, B. T., & Ovens, H. J. (2002). Frequent users of emergency departments. Do they also use family physicians' services? *Canadian Family Physician, 48*(10), 1654-1660.

Cook, L. J., Knight, S., Junkins, E. P., Mann, N. C., Dean, J. M., & Olson, L. M. (2004). Repeat patients to the emergency department in a statewide database. *Academic Emergency Medicine, 11*, 256-263. doi: 10.1111/j.1553-2712.2004.tb02206.x

Doupe, M. B., Palatnick, W., Day, S., Chateau, D., Soodeen, R. A., Burchill, C., & Derksen, S. (2012). Frequent users of emergency departments: developing standard definitions and defining prominent risk factors. *Annals of Emergency Medicine, 60*, 24-32. doi: 10.1016/j.annemergmed.2011.11.036.

Fuda, K. K., & Immekus, R. (2006). Frequent users of Massachusetts emergency departments: A statewide analysis. *Annals of Emergency Medicine, 48*, 16-e1. doi: 10.1016/j.annemergmed.2006.03.001

Goniewicz, M. (2013). Effect of military conflicts on the formation of emergency medical services systems worldwide. Academic Emergency Medicine, 20, 507-513. doi: 10.1111/acem.12129

Hansagi, H., Olsson, M., Sjoberg, S., Tomson, Y., & Goransson, S. (2001). Frequent use of the hospital emergency department is indicative of high use of other health care services. *Annals of Emergency Medicine, 37*, 561–7. doi: 10.1067/mem.2001.111762

Huang, J.A., Tsai, W.C., Chen, Y.C., Hu, W.H., Yang, D.Y. (2003). Factors associated with frequent use of emergency services in a medical center. *Journal of the Formosan Medical Association, 102*(4), 222–8.

Hunt, K.A., Weber, E.J., Showstack, J.A., Colby, D.C., & Callaham, M.L. (2006). Characteristics of frequent users of emergency departments. *Annals of Emergency Medicine, 48*, 1–8. doi: 10.1016/j.annemergmed.2005.12.030

Institute of Medicine (IOM). (2006). *Hospital based emergency care: At the breaking point*. Washington (DC): National Academies Press.

Krieg, C., Hudon, C., Chouinard, M. C., & Dufour, I. (2016). Individual predictors of frequent emergency department use: A scoping review. *BMC Health Services Research, 16*, 594. doi: 10.1186/s12913-016-1852-1

LaCalle, E., & Rabin, E. (2010). Frequent users of emergency departments: The myths, the data, and the policy implications. *Annals of Emergency Medicine, 56*, 42–48. doi:10.1016/j.annemergmed.2010.01.032

Mandelberg, J. H., Kuhn, R. E., & Kohn, M. A. (2000). Epidemiologic analysis of an urban, public emergency department's frequent users. *Academic Emergency Medicine, 7*(6), 637-646.

McCaig, L.F., Stussman, B.J. (1996). National hospital ambulatory medical care survey: 1996 emergency department summary. *Advance Data, 293*, 1-20. Retrieved from https://www.cdc.gov/nchs/data/ad/ad293.pdf

Moore, G., Gerdtz, M., Manias, E., Hepworth, G., & Dent, A. (2007). Socio-demographic and clinical characteristics of re-presentation to an Australian inner-city emergency department: Implications for service delivery. *BMC Public Health, 7*, 320. doi: 10.1186/1471-2458-7-320

Nakao, H., Ukai, I., & Kotani, J. (2017). A review of the history of the origin of triage from a disaster medicine perspective. *Acute Medicine & Surgery, 4,* 379–384. doi: 10.1002/ams2.293

National Academy of Sciences (NAS). (1966). *Accidental death and disability: The neglected disease of modern society*. Washington, DC. Retrieved from https://www.ems.gov/pdf/1997-Reproduction-AccidentalDeathDissability.pdf

National Center for Health Statistics, Ambulatory and Hospital Care Statistics Branch. (2009). *Ambulatory health care data*. Retrieved from http:// www.cdc.gov/nchs/ahcd.htm

Naughton, C., Drennan, J., Treacy, P., Fealy, G., Kilkenny, M., Johnson, F., & Butler, M. (2010). The role of health and non-health-related factors in repeat emergency department visits in an elderly urban population. *Emergency Medicine Journal, 27*, 683-687. doi: 10.1136/emj.2009.077917

Palmer, E., Leblanc-Duchin, D., Murray, J., & Atkinson, P. (2014). Emergency department use: Is frequent use associated with a lack of primary care provider? *Canadian Family Physician, 60*(4), e223-e229.

Pitts, S. R., Carrier, E. R., Rich, E. C., & Kellermann, A. L. (2010). Where Americans get acute care: Increasingly, it's not at their doctor's office. *Health affairs, 29*, 1620-1629. doi: 10.1377/hlthaff.2009.1026.

Schuur, J.D., Venkatesh, A.K. (2012). The growing role of emergency departments in hospital admissions. *New England Journal of Medicine, 367*, 391-393. doi: 10.1056/NEJMp1204431

Sun, B. C., Burstin, H. R., & Brennan, T. A. (2003). Predictors and outcomes of frequent emergency department users. *Academic Emergency Medicine, 10*(4), 320-328.

Suter, R.E. (2012). Emergency medicine in the United States: A systemic review. World Journal of Emergency Medicine, 3, 5-10. doi: 10.5847/wjem.j.issn.1920-8642.2012.01.001

Tang, N., Stein, J., Hsia, R.Y., Maselli, J.H., Gonzales, R. (2010). Trends and characteristics of US emergency department visits, 1997-2007. *Journal of the American Medical Association, 304*, 664-70. doi: 10.1001/jama.2010.1112.

To amend title XIX of the Social Security Act to reduce unnecessary emergency room visits under the Medicaid program, 1323, 115th Cong. (2017).

vonBertalanffy, L. (1968). General systems theory: Foundations, development, applications. New York: George Braziller.

Weber, E. J. (2012). Defining frequent use: The numbers no longer count. *Annals of Emergency Medicine, 60,* 33-34. doi: 10.1016/j.annemergmed.2012.02.019

Wisconsin Senate. (2018). An act to create 49.45 (26g), 946.91 (3) (c) 3. and 946.93 (5) (c) 3. of the statutes; relating to: Intensive care coordination program in the Medical Assistance program, 742. Retrieved from https://docs.legis.wisconsin.gov/2017/related/proposals/sb742/1/_6

Zuckerman, S., & Shen, Y. C. (2004). Characteristics of occasional and frequent emergency department users: Do insurance coverage and access to care matter? *Medical Care, 42*, 176-182. doi: 10.1097/01.mlr.0000108747.51198.41

CHAPTER 2: WALKING BEYOND THE STRAIGHT AND NARROW: EMERGENCY DEPARTMENT UTILIZATION THROUGH A SYSTEMIC LENS

Nearly nineteen percent (18.8%) of U.S. adults age eighteen years or older visit the emergency department (ED) in a given year (Centers for Disease Control, 2016). A small portion (~ 8%) of these account for many visits (28%), when defined as four or more visits in one year (so-called "frequent users"; Hunt, Weber, Showstack, Colby, & Callahan, 2006). Frequent ED users have been the focus of media attention, research, and policy discussions; however, it remains unclear whether assumptions about this population are supported by data (LaCalle & Rabin, 2010; Weber, 2012). Understanding this population is complex, as frequent ED users are a heterogeneous group. Although early literature posited that frequent users visit the ED unnecessarily (Malone, 1995; Malone, 1998; Spillane et al., 1997), more recent evidence has demonstrated that this population has many health needs (Fuda & Immekus, 2006; Hunt et al., 2006; Sandoval et al., 2010), requires many healthcare services (Peppe, Mays, Chang, Becker, & DiJulio, 2007), and may have episodic patterns of use (Fuda & Immekus, 2006), which possibly include healthcare emergencies such as episodes related to chronic health conditions (Doupe et al., 2012).

Despite the systemic complexity that seems to characterize frequent ED use, the literature has almost exclusively defined this experience in a linear, unidimensional fashion, based solely on the number of ED visits a person makes (Goodman et al., 2018). The way in which frequent ED use is defined informs research design, types of interventions, popular media portrayals, and healthcare policies. As such, it is important to understand how this linear, unidimensional way of defining frequent ED use impacts our understanding of both frequent use and the approaches taken to address it. Therefore, the purpose of this literature review is to (a) describe how linear

based perspectives on ED utilization limit the potential understanding of a growing healthcare concern or propel research, interventions, popular media publication portrayals and policy; (b) explore the potential for systemic definitions of this phenomenon.

Research on Frequent Use

In the biomedical literature, the definitions for frequent ED use seem to vary greatly (Doupe et al., 2012). For example, Lee and Davenport (2006) defined frequent use as three or more visits in one month, while others have used definitions such as 20 or more visits in a year (LaCalle, 2013), two to twenty visits in a year (Ruger, Richter, Spitznagel, & Lewis, 2004), top ten percent of ED users in a given year (Chambers et al., 2013), or two standard deviations above the mean number of visits (Pasic, Russo, & Roy-Byrne, 2005). Without a standardized definition, it is difficult to draw generalized findings or conclusions about this population.

Defining Frequent Use

The justifications given for definitions of frequent ED use vary as widely as the definitions of frequent ED use themselves. Even for a given definition, the justifications provided for operationalizing the concept in a certain way vary. For example, Goodman and colleagues (2018) found that the definition of frequent ED use among a general population was most frequently cited in literature as four or more visits in one year and there were no fewer than four justifications commonly used in the literature to support this operationalization. These justifications included (a) no justification at all; (b) common definition (i.e., the authors selected it because it was commonly used in other literature on the topic); (c) citation of literature was provided without further explanation; (d) based on empirical study data. Most troubling is that the largest proportion of all peer-reviewed research articles from 1981 to 2017 on frequent ED use (45.1%) provided no justification, including neither rationale nor citation to support the

definition they used (Goodman et al., 2018). When justifications were provided, researchers often stated that the selected definition was "common" in the literature and/or then cited literature without further explanation; this was reflected in half of the definitions used. Interestingly, the most common definition used in the literature (i.e., ≥ 4 visits in one year), was originally selected because it was thought that targeting individuals with this amount of use would reduce ED overcrowding (Cook et al., 2004; Hunt et al., 2006; Naughton et al., 2010; Sun, Burstin, & Brennan, 2003). The absence of a clear justification for any given definition points to the lack of value placed on how frequent ED use is operationalized and also has the potential to disrupt the integrity of the research surrounding the "chosen" definition.

Although frequent ED users have commonly been found to have greater healthcare needs and healthcare utilization across the continuum of care (e.g. from primary through specialty care) than other ED users, the characteristics of this population are diverse, yet bound to the sampling and definitions used to operationalize this concept (Byrne, 2003; Chan & Ovens, 2002; Fuda & Immekus, 2006; Hansagi et al., 2001; Hunt, Weber, Showstack, Colby, & Callaham, 2006; Weber, 2012; Zuckerman & Shen, 2004) . The number of visits used to define the phenomenon influences the characteristics that a given group of frequent ED users are found to possess. For example, studies with higher thresholds for frequent ED use (i.e., Althaus et al., 2013 with twelve visits per year; Skinner, Carter, & Haxton, 2009, with ten visits per year) tend to report that patients that meet this criterion have higher levels of primary care enrollment than patients in studies with lower thresholds for defining frequent ED use (i.e., Bieler et al., 2012, with four visits per year). Likewise, different characteristics are noted depending on the sample. Van Tiel and colleagues (2015) observed that in U.S. studies, frequent ED users tend to have higher acuity

and more frequent admissions than non-frequent users, while in international studies the opposite is the case, with frequent ED users exhibiting lower acuity than non-frequent users.

In a recent systematic review, Goodman and colleagues (2018) found that only two-and-a-half percent of the articles included in their study used empirical means to define frequent users. These studies attempted to categorize frequent ED users based on patient characteristics, rather than allowing a particular number of visits to either guide their analysis or define frequent ED use outright. Two of these articles attempted to create objective thresholds for frequent ED use (Doupe et al., 2012; Locker, Baston, Mason, & Nicholl, 2007). Ultimately, such methods have resorted to choosing a numeric threshold or "breakpoint" even though patient characteristics exist along a continuum, and do not fit neatly into numeric visit ranges established by researchers (i.e., mental health diagnoses may be present in the frequent user population but are also present in the non-frequent user population as well). This demonstrates that frequent use exists along a continuum, and that mathematical and descriptive definitions of frequent ED use (i.e., establishing breakpoints or using a number of ED visits) are an oversimplification (Weber, 2012). Further, using a mathematical or descriptive numeric definition of frequent use eschews the fact that many frequent users may be quite sick, and require more healthcare resources (Byrne et al., 2003; Chan & Ovens, 2002; Hansagi et al., 2001), making the ED an appropriate context for care.

Interventions for Frequent Use

Beyond the outcome research associated with defining frequent ED use, is the research focused on interventions to reduce frequent ED use. The most frequently tested intervention to reduce ED visits among frequent ED users is case management (Althaus et al., 2011; Lee & Davenport, 2006; Phillips et al., 2006; Pope et al., 2000; Shumway et al., 2008; Skinner, Carter,

& Haxton, 2009; Wassmer, Winward, & Derlet, 2010). Continuing with the concern related to linear and unidimensional ways of understanding frequent ED use, the research intervention studies used number of visits to the ED (ranging from three or more per year to five or more per month) as the measure of frequent ED use, and chiefly based their outcome measures on a reduction in these visits (Pope et al., 2000; Shumway et al., 2008; Skinner, Carter, & Haxton, 2009; Wassmer, Winward, & Derlet, 2010). Two of these studies also examined reduction in the cost of services (Shumway et al., 2008; Wassmer, Winward, and Derlet, 2010).

These studies found that certain aspects of case management interventions seem to correlate with reduced visits and lower costs, including (a) frequency of follow-up with case managers after the initial interview; (b) availability of psychosocial services such as substance abuse counseling; (c) assistance with attainment of financial entitlements; (d) the aggressiveness of outreach to participants (Kumar & Klein, 2013). For example, studies that described case managers as actively involved in identifying patients on the streets or in their homes (Phillips et al., 2006), meeting with patients regularly (Shumway et al., 2008), or accompanying them to their appointments (Wassmer, Winward, & Derlet, 2008), demonstrated significant reductions in ED visits. However, these articles make no mention of whether the patients in their studies have improved health outcomes (or other outcomes) as a result of these interventions. Likewise, many of these interventions are implemented for, and measure outcomes based on one year of data only, despite evidence suggesting that the majority of frequent ED users cease to visit the ED frequently after one year without any intervention (Mandelberg, Kuhn, & Kohn, 2000).

The literature demonstrates that frequent ED use has been defined largely without empirical means, and limited justification. Moreover, the characteristics of individuals who have been labeled as frequent ED users vary depending on the sample, and the definition used to

operationalize this phenomenon. Despite such evidence, frequent ED users continue to be portrayed in research literature as a homogenous group. As such, one-size-fits-all interventions, involving case management have largely been employed with the goal of reducing the number of visits, rather than focusing on how unique characteristics should inform interventions and target the improvement of outcomes.

Media on Frequent Use

On some level, the media's portrayal of frequent ED use has guided readers into thinking that a systemic lens (not a linear perspective) has grounded the definition and sample of frequent users. After all, some journalists even highlight that numerous social determinants of health, such as poverty, homelessness, etc. have an impact on health and healthcare utilization. However, this falls flat for two reasons (a) there is no theory-driven research cited within media articles to support such claims; (b) the way frequent ED use is defined in the media is still reduced to the linear, unidimensional factor of frequent ED use (i.e., 60-80 ED visits per year; WMCActionNews5.com Staff, 2017). For example, an article about the Michigan Blueprint System, talks about patient interventions that attend to social determinants of health (e.g., homelessness and hunger), but uses the threshold of five or more visits in a year to define the targeted group (Grimes, 2016). The justification given in the article for this definition is that those with this level of use (i.e., five or more visits) tend to experience substance abuse, mental health concerns, and homelessness resulting in the frequent ED use. Another article addresses the need to understand the real reasons for which patients make sixty to eighty visits a year to the ED but makes no mention of why they selected that threshold of use other than that it was a large number of ED visits (WMCActionNews5.com Staff, 2017). In a third example, Zimmerman (2017) put forth an article about a program in Connecticut, using hospital data to suggest that

people cycling through the ED often have mental health or substance abuse problems. However, the journalist based the identification of patients on the number of ED visits that the patients engage in, without clarifying the number of ED visits used as the criterion for this assessment, or how the hospital system arrived at this unknown number (Zimmerman, 2017). News broadcasters have characterized frequent users as those who have visited the ED more than one-hundred times in a year and suggest that they are individuals who more commonly experience homelessness, complicated medical conditions, and chronic diseases (10news.com, 2017). While characterizing "frequent fliers" as those with one-hundred visits or more in a year without providing justification for this definition, they also suggest that these individuals are increasing the cost burden to the system because they are uninsured yet do not cite research evidence to support that this is truly the case.

While media reports have attended to social determinants of health, and their influence on health and healthcare utilization, the interventions these stories highlight are targeted toward reducing the number of visits made by individuals with a certain threshold of use. This is done without regard for whether this is an appropriate goal for each patient, or the complexity for the patients' social determinants of health. Moreover, not unlike the biomedical research articles, media reports lack empirical justification for the way they define and describe frequent ED use. Most commonly, media publications define use in a unilevel fashion, based on the number of visits an individual makes to the ED, typically within a given year (10news.com, 2017; Grimes, 2016; WMCActionNews5.com Staff, 2017). Such characterizations reinforce to the public that both the problem of and solution for frequent ED use is framed in the context of how many visits an individual makes to the ED, and that those making a higher number of visits are doing so unnecessarily.

Policy on Frequent Use

Not unlike biomedical researchers, policy researchers make an effort to describe the characteristics of frequent ED users, but then unilaterally operationalize the phenomenon using number of visits (Billings & Raven, 2013; Buhumaid, Riley, Sattarian, Bregman, & Blanchard, 2015; Colligan, Pines, Colantuoni, & Wolff, 2017; Cunningham, 2006; Leporatti, Ameri, Trinchero, Orcamo, & Montefiori, 2016; Shapiro, 2013; Soril, Leggett, Lorenzetti, Noseworthy, & Clement, 2016; Wise-Harris, 2016). Instead of using patient characteristics to help define and operationalize frequent ED use, these factors are examined by the number of visits made. For example, aims of such policy research articles include (a) measuring incremental increase in the number of frequent ED users when utilization data is shared across hospitals (Shapiro, 2013); (b) identifying common sociodemographic and clinical characteristics of frequent ED users (Buhumaid et al., 2015; Colligan et al., 2017; Leporatti et al., 2016; Soril et al., 2016); (c) identifying whether there is any variation in number of visits across communities, given certain patient characteristics at the aggregate level—such as percent of patients uninsured, Hispanic, or non-citizen (Cunningham, 2006); (d) developing predictive modeling to identify who will become a frequent user (Billings & Raven, 2013).

The aforementioned policy research articles posit recommendations largely focused on reducing the number of ED visits through such strategies as (a) targeted case management and other services (Shapiro, 2013); (b) extending primary care hours (Leporatti et al., 2016); (c) increasing access to or types of social services; (d) ensuring proper equipment is available; (e) development and access to patient education; (f) developing alternative models of care (e.g., more accessible community care, emergency care sensitive to the needs of frequent users; Wise-Harris, 2016); (g) adding staff training (e.g., to prevent provider burnout and compassion fatigue

related to care for this population); (h) evaluating how payment policy can encourage better care coordination (Colligan et al., 2017). Such recommendations attempt to expand beyond the efforts made in the biomedical literature, which largely focus on case management. However, if the goal remains to reduce number of ED visits, this is likely neglecting the bigger question: should the policy focus be on reduction in visits (alone), or is it more appropriate to attend to the ways in which health outcomes or quality of care are improved for frequent users?

In fact, there are a number of policies that provide incentives to hospitals to reduce the number of ED visits by a given patient. For example, a 2017-2018 Wisconsin state senate bill proposes that the Department of Health Services provide up to $1,000 per patient enrolled in the state's Medical Assistance program, per year, (up to $1,500,000) to any given program that demonstrates progress in reducing emergency department visits for at least half of its enrollee population (Wisconsin, 2018). The bill also states that participating organizations can measure outcomes such as successful connection to primary care or a managed care organization (as evidenced by 2 or 3 primary care appointments) and/or to behavioral health and substance abuse treatment or support. Measuring primary care visits or use of behavioral and substance use resources on the onset may appear as though it is better attending to the systemic complexity of frequent ED use. Yet, policy researchers have demonstrated that frequent ED users are actually more likely to visit primary care than non-frequent users (Chan & Ovens, 2002; Hansagi, Olsson, Sjöberg, Tomson, & Göransson, 2001), and substance abuse is only one of many characteristics that may be an issue for a frequent ED user. Therefore, rather than encouraging a mere shift to other healthcare services, new policies to address frequent ED use, based on empirical research that takes into account systemic factors associated with emergency department use (e.g., biopsychosocial attributes such as income, race, geographic location), need to be created.

It is worth noting that organizations who engage in incentive plans will be rewarded for achieving a reduction in number of ED visits, but it is possible that this could be done without any improvement in patients' health outcomes. The cost of implementing programs (e.g., longer PCP hours, case management) based on arbitrary assumptions (e.g., the number of visits to the ED a patient makes in a given year), may result in increased expenditures for the organization with little, if any, effect on the presenting problem (improvements to the patients' health). Even if there are positive benefits, it is difficult to assign success to certain programs if the relationships between action and ED utilization are unknown. Therefore, measuring success non -systemic manner may result in unsubstantiated spending increases or reductions in operational continuity within the healthcare organization. These points highlight some of the risks associated with measuring ED use in a unidimensional fashion, based on number of visits: (a) health systems may be wasting resources by reducing the number of visits for individuals who have episodic care needs and would have ceased to use the ED frequently on their own once sufficiently treated; and (b) there is currently no empirical data to indicate that reducing the number of ED visits a patient makes will improve his or her health outcomes. Moreover, given that it is unknown whether patient outcomes will improve, stay the same, decline, or if such outcomes will vary across patients as the number of ED visits they make decreases, there is a risk that policies incentivizing a decrease in ED visits could negatively impact patient health, and thus also be an inappropriate allocation of resources.

Implications: The Potential for A Systemic Approach to Operationalizing Frequent ED Use

The way in which frequent ED use is defined informs the research done to understand both this phenomenon, its outcomes, and the types of interventions and policies that are created to address it. It is essential that research, interventions, and policies designed to address the needs

of ED users be grounded in systems theory and informed by systemic patient data. The Andersen Model (1995) offers a framework through which to understand frequent ED use, as it takes into account many factors that inform healthcare use (e.g. demographics, family support). However, unlike systems theory, the Anderson Model ultimately evaluates these factors at the intra-individual level and does not fully account for the circular and bidirectional nature of the many factors that simultaneously contribute to ED use. A systemic, bidirectional understanding of frequent ED use would allow for a wholistic consideration of all patient characteristics, rather than a summative intrapersonal perspective. The use of systems theory would help to move researchers and policy makers away from the linear approaches currently used to describe frequent ED users and this complex phenomena through a more comprehensive lens.

As previously mentioned, the current definition of frequent ED use employs a linear, unilevel definition based on number of ED visits. Using a linear lens to conduct research, create interventions, disseminate information in the media, and form policy perpetuates a nonsummative understanding of patients. By identifying ED patient subgroups based on systemic patient characteristics, researchers could examine whether patients in each of these distinct subgroups are receiving the types of care they need, and which interventions are associated with better outcomes within a given subgroup. Treatments and interventions could then be informed by these findings and tailored to the systemic, relational, and familial needs of each patient. It is also critical that media portrayals on ED use do no perpetuate disproven and unfounded myths about frequent utilizers, but instead cite empirical research regarding the characteristics of this group. Finally, the policies that address ED use should be tailored to unique ED patient subgroups and punctuate the use of protocols that employ best practices grounded in intervention research.

Conclusion

While there is undoubtedly a group that experiences a higher frequency of ED use, both the way "frequent ED use" has been defined and the "problem" (as it has been framed in terms of ED use), has ubiquitously focused on number of visits, in a linear, unidimensional fashion. This has resulted in research, interventions, media portrayals, and policy that examine both the phenomenon and patients through the lens of whether they have visited "too many" times, and measures outcomes based on the goal of reducing the number of visits rather than examining whether use was appropriate, patients have received appropriate kinds of care, or their service needs were met, for example.

We have, however, gained an important perspective from the linear approach to ED use, which focuses on the number of ED visits alone. For example, we understand that there is a population of individuals that visit the ED at a higher rate than the general population, and these individuals have greater healthcare needs (Byrne et al., 2003; Fuda & Immekus, 2006; Hunt, Weber, Showstack, Colby, & Callahan, 2006), and greater overall healthcare usage across healthcare services (e.g. primary care, specialty care, etc.; Byrne et al., 2003; Chan & Ovens, 2002; Hansagi, Olsson, Sjöberg, Tomson, & Göransson, 2001). However, this linear focus eschews the fact that ED use, including frequent use, exists along a continuum, and a unilevel descriptive definition of this issue is an oversimplification at best (Weber, 2012).

A linear approach to ED use has highlighted the need for a new, systemic approach to understanding ED use. Such an approach, based in systems theory (vonBertalanffy, 1968), would allow us to expand beyond a unilevel understanding of use, to incorporate as many systemic levels as possible, including things such as patient demographics, geographic information, diagnoses, interventions, etc. This new approach would not happen within the frame of a number

of visits, but rather, this approach would allow multiple systemic levels to be considered together in order to see which patient characteristics coalesce to form unique patient cohorts.

REFERENCES

10news.com. (2017). *Report: Overuse of Local ERs Costing Millions.* Retrieved from https://www.10news.com/news/report-overuse-of-local-ers-costing-millions

Althaus, F., Paroz, S., Hugli, O., Ghali, W. A., Daeppen, J., Peytremann-Bridevaux, I., & Bodenmann, P. (2011). Effectiveness of interventions targeting frequent users of emergency departments: A systematic review. *Annals of Emergency Medicine, 58*, 41-52.e42. doi:10.1016/j.annemergmed.2011.03.007

Althaus, F., Stucki, S., Guyot, S., Trueb, L., Moschetti, K., Daeppen, J.B., Bodenmann, P. (2013).Characteristics of highly frequent users of a Swiss academic emergency department: A retrospective consecutive case series. *European Journal of Emergency Medicine, 20*, 413–419. doi: 10.1097/MEJ.0b013e32835e078e

Bieler, G., Paroz, S., Faouzi, M., Trueb, L., Vaucher, P., Althaus, F., ... & Bodenmann, P. (2012). Social and medical vulnerability factors of emergency department frequent users in a universal health insurance system. *Academic Emergency Medicine, 19*, 63-68. doi: 10.1111/j.1553-2712.2011.01246.x

Billings, J., & Raven, M. C. (2013). Dispelling an urban legend: Frequent emergency department users have substantial burden of disease. *Health Affairs, 32*, 2099-2108. doi: 10.1377/hlthaff.2012.1276

Buhumaid, R., Riley, J., Sattarian, M., Bregman, B., & Blanchard, J. (2015). Characteristics of frequent users of the emergency department with psychiatric conditions. *Journal of Health Care for the Poor and Underserved, 26*, 941-950. doi: 10.1353/hpu.2015.0079

Byrne, M., Murphy, A.W., Plunkett, P.K., McGee, H.M., Murray, A., Bury, G. (2003). Frequent attenders to an emergency department: A study of primary health care use, medical profile, and psychosocial characteristics. *Annals of Emergency Medicine, 41*, 309–318. doi: 10.1067/mem.2003.68

Centers for Disease Control (2016). *Health, United States, 2016: With chartbook on long-term trends in health*. Retrieved from: https://www.cdc.gov/nchs/data/hus/hus16.pdf#076

Chan, B. T., & Ovens, H. J. (2002). Frequent users of emergency departments. Do they also use family physicians' services? *Canadian Family Physician, 48*(10), 1654-1660.

Colligan, E. M., Pines, J. M., Colantuoni, E., & Wolff, J. L. (2017). Factors associated with frequent emergency department use in the Medicare population. *Medical Care Research and Review, 74*, 311-327. doi:10.1177/1077558716641826

Cunningham, P. J. (2006). What accounts for differences in the use of hospital emergency departments across U.S. communities? *Health Affairs, 25*, w324-w336. doi:10.1377/hlthaff.25.w324

Doupe, M. B., Palatnick, W., Day, S., Chateau, D., Soodeen, R. A., Burchill, C., & Derksen, S. (2012). Frequent users of emergency departments: Developing standard definitions and defining prominent risk factors. *Annals of Emergency Medicine, 60*, 24-32. doi: 10.1016/j.annemergmed.2011.11.036

Fuda, K. K., & Immekus, R. (2006). Frequent users of Massachusetts emergency departments: A statewide analysis. *Annals of Emergency Medicine, 48*, 16-e1. doi: 10.1016/j.annemergmed.2006.03.001

Grimes, R. (2016). *Project aims to reduce emergency room "frequent fliers" by tackling underlying social issues*. Retrieved from http://michiganradio.org/post/project-aims-reduce-emergency-room-frequent-fliers-tackling-underlying-social-issues

Hansagi, H., Olsson, M., Sjöberg, S., Tomson, Y., Göransson, S. (2001). Frequent use of the hospital emergency department is indicative of high use of other health care services. *Annals of Emergency Medicine, 37,* 561–567. doi: 10.1067/mem.2001.111762

Hansagi, H., Olsson, M., Hussain, A., Ohlén, G. (2008). Is information sharing between the emergency department and primary care useful to the care of frequent emergency department users? *European Journal of Emergency Medicine, 15,* 34–39. doi: 10.1097/MEJ.0b013e3282aa4115

Hunt, K. A., Weber, E. J., Showstack, J. A., Colby, D. C., & Callaham, M. L. (2006). Characteristics of frequent users of emergency departments. *Annals of Emergency Medicine, 48*, 1-8. doi: 10.1016/j.annemergmed.2005.12.030

Kumar, G. S., & Klein, R. (2013). Effectiveness of case management strategies in reducing emergency department visits in frequent user patient populations: A systematic review. *The Journal of Emergency Medicine, 44*(3), 717-729. doi: 10.1016/j.jemermed.2012.08.035

LaCalle, E. J., Rabin, E. J., & Genes, N. G. (2013). High-frequency users of emergency department care. *The Journal of Emergency Medicine, 44*, 1167-1173. doi: 10.1016/j.jemermed.2012.11.042

Lee, K. H., & Davenport, L. (2006). Can case management interventions reduce the number of emergency department visits by frequent users? *The Health Care Manager, 25*(2), 155-159.

Leporatti, L., Ameri, M., Trinchero, C., Orcamo, P., & Montefiori, M. (2016). Targeting frequent users of emergency departments: Prominent risk factors and policy implications. *Health Policy, 120*, 462-470. doi: 10.1016/j.healthpol.2016.03.005

Malone, R. E. (1995). Heavy users of emergency services: social construction of a policy problem. *Social Science & Medicine*, *40*(4), 469-477.

Malone, R. E. (1998). Whither the almshouse? Overutilization and the role of the emergency department. *Journal of Health Politics, Policy and Law*, *23*(5), 795-832.

Pasic, J., Russo, J., & Roy-Byrne, P. (2005). High utilizers of psychiatric emergency services. *Psychiatric Services, 56*, 678-684. doi: 10.1176/appi.ps.56.6.678

Peppe, E.M., Mays, J.W., Chang, H.C., Becker, E. & DiJulio, B. (2007). Characteristics of frequent emergency department users. *The Henry J. Kaiser Family Foundation*. Retrieved from https://pdfs.semanticscholar.org/6ca4/c91f1307c43d72362edf462b81899605067f.pdf

Phillips, G. A., Brophy, D. S., Weiland, T. J., Chenhall, A. J., & Dent, A. W. (2006). The effect of multidisciplinary case management on selected outcomes for frequent attenders at an emergency department. *The Medical Journal of Australia, 184*(12), 602-606.

Pope, D., Fernandes, C. M., Bouthillette, F., & Etherington, J. (2000). Frequent users of the emergency department: A program to improve care and reduce visits. *Canadian Medical Association Journa*l, *162*(7), 1017-1020.

Ruger, J. P., Richter, C. J., Spitznagel, E. L., & Lewis, L. M. (2004). Analysis of costs, length of stay, and utilization of emergency department services by frequent users: Implications for health policy. *Academic Emergency Medicine, 11*, 1311-1317. doi: 10.1197/j.aem.2004.07.008

Sandoval, E., Smith, S., Walter, J., Schuman, S. A. H., Olson, M. P., Striefler, R., ... & Hickner, J. (2010). A comparison of frequent and infrequent visitors to an urban emergency department. *The Journal of Emergency Medicine, 38*, 115-121. doi: 10.1016/j.jemermed.2007.09.042

Shapiro, J. S., Johnson, S. A., Angiollilo, J., Fleischman, W., Onyile, A., & Kuperman, G. (2013). Health information exchange improves identification of frequent emergency department users. *Health Affairs, 32*, 2193-2198. doi: 10.1377/hlthaff.2013.0167

Shumway, M., Boccellari, A., O'Brien, K., & Okin, R. L. (2008). Cost-effectiveness of clinical case management for ED frequent users: Results of a randomized trial. *American Journal of Emergency Medicine, 26*, 155-164. doi:10.1016/j.ajem.2007.04.021

Skinner, J., Carter, L., & Haxton, C. (2009). Case management of patients who frequently present to a Scottish emergency department. *Emergency Medicine Journal, 26*, 103-105. doi: 10.1136/emj.2008.063081

Soril, L. J. J., Leggett, L. E., Lorenzetti, D. L., Noseworthy, T. W., & Clement, F. M. (2016). Characteristics of frequent users of the emergency department in the general adult population: A systematic review of international healthcare systems. *Health Policy, 120*, 452-461. doi:10.1016/j.healthpol.2016.02.006

Spillane, L. L., Lumb, E. W., Cobaugh, D. J., Wilcox, S. R., Clark, J. S., & Schneider, S. M. (1997). Frequent users of the emergency department: Can we intervene? *Academic Emergency Medicine*, *4*(6), 574-580.

Sun, B. C., Burstin, H. R., & Brennan, T. A. (2003). Predictors and outcomes of frequent emergency department users. *Academic Emergency Medicine, 10*(4), 320-328.

van Tiel, S., Rood, P. P., Bertoli-Avella, A. M., Erasmus, V., Haagsma, J., van Beeck, E., ... & Polinder, S. (2015). Systematic review of frequent users of emergency departments in non-US hospitals: State of the art. *European Journal of Emergency Medicine, 22*, 306-315. doi: 10.1097/MEJ.0000000000000242

vonBertalanffy, L. (1968). General systems theory: Foundations, development, applications. New York: George Braziller.

Wassmer, R.W., Winward, L., Derlet, R. (2008). Does counseling reduce frequent emergency department use? Retrieved from http:// papers.ssrn.com/sol3/papers.cfm?abstract_id=1093870

Weber, E. J. (2012). Defining frequent use: The numbers no longer count. *Annals of Emergency Medicine, 60*, 33-34. doi: 10.1016/j.annemergmed.2012.02.019

Wisconsin 2017 Senate Bill 742. (2018). An act to create 49.45 (26g), 946.91 (3) (c) 3. and 946.93 (5) (c) 3. of the statutes; relating to: intensive care coordination program in the Medical Assistance program. Retrieved from http://docs.legis.wisconsin.gov/2017/related/proposals/sb742.pdf

Wise-Harris, D., Pauly, D., Kahan, D., de Bibiana, J. T., Hwang, S. W., & Stergiopoulos, V. (2017). "Hospital was the only option": Experiences of frequent emergency department users in mental health. *Administration and Policy in Mental Health and Mental Health Services Research, 44*, 405-412. doi:10.1007/s10488-016-0728-3

WMCActionNews5.com Staff. (2017). *Hospitals offer solution to high ER wait times.* Retrieved from http://www.live5news.com/story/36142431/hospitals-offer-solution-to-high-er-wait-times

Zimmerman, K. (2017). *Norwalk health center exploring new approach to repeat ER users*. Retrieved from https://westfaironline.com/85329/norwalk-health-center-exploring-new-approach-to-repeat-er-users/

CHAPTER 3: OPERATIONALIZING FREQUENT ED USE: A SYSTEMATIC REVIEW

Frequent emergency department (ED) users have been the focus of media attention, research, and policy discussions, however it remains unclear whether assumptions about this population are supported by data (LaCalle & Rabin, 2010). Health policy leaders and emergency providers in many countries have been interested in the trends of these patients, not only because of costs and overcrowding in the ED, but also because of the complex medical and social needs they present with (Chan & Ovens, 2002; Hansagi, Olsson, Sjoberg, Tomson, & Goransson, 2001; Hunt, Weber, Showstack, Colby, & Callaham, 2006; LaCalle & Rabin, 2010; Moore, Gerdtz, Manias, Hepworth, & Dent, 2007). Understanding this population is complex, as frequent ED users are a heterogeneous group, commonly with greater healthcare needs and healthcare utilization across a continuum of care (e.g. from primary through specialty care; Byrne, 2003; Chan & Ovens, 2002; Fuda & Immekus, 2006; Hansagi et al., 2001; Hunt,Weber, Showstack, Colby, & Callaham, 2006; Weber, 2012; Zuckerman & Shen, 2004) than other ED users. Adding to this complexity, are the inconsistent patterns of use; some have episodic patterns of use while others have frequent utilization over a specified time frame. A proportion of frequent users appear to stop using the ED without receiving treatment (Doupe et al., 2012; Fuda & Immekus, 2006; Kne, Young, & Spillane, 1998; Mandelberg, Kuhn, & Kohn, 2000).

The way in which frequent ED use is defined informs research design, types of interventions, and healthcare policies. However, prior to conducting the systematic review for this manuscript, a review of the literature quickly led to curiosity about whether research, policies, and interventions that are designed to address the needs of ED users are data informed or grounded in theory. Numerous systematic reviews have been conducted that explore the characteristics of frequent ED utilization (e.g. Moe et al., 2016; Soril, Leggett, Lorenzetti,

Noseworthy, & Clement, 2016; van Tiel, 2015), yet it is concerning that no literature appears to exist on a theoretically grounded and data informed definition for frequent utilization. As such, the purpose of our article is to offer a systematic review that (a) evaluates the existing definitions of frequent ED utilization and (b) identifies the evidence used to support the existing definitions.

The framework that serves as the foundation for this systematic review is general systems theory (vonBertalanffy, 1968). This theory was selected because it emphasizes the need to understand the context in which an event or behavior is occurring in order to make sense of the phenomenon. Specifically, systems theory posits that a system cannot be understood by only studying components individually, but rather should be explored and analyzed via the interactions of its components and the nonlinearity of those interactions. In the context of defining frequent utilization of the ED, this means that utilization should not be reduced to individual factors (e.g., characteristics of use or a social location of the patient population), but instead must look at how these individual components interact with one another to reflect a holistic view of what comprises and influences ED use. This does not negate the importance of individual components, but rather suggests that they should not be used in isolation to form the definition for frequent utilization.

Systems theory includes many comprehensive constructs that are relevant to better understanding the definition of frequent utilization. Given the space limitations for this manuscript, only two constructs will be described (nonsummativity and static teleology; vonBertalanffy, 1968). Systemists often state that to understand the specific systemic qualities and behavior on a certain level, it is necessary to study the levels above and below the chosen level. As such, one key construct from systems theory is nonsummativity. The rule of

nonsummativity states that the sum of the whole system is greater or different than the sum of its parts. Applied to the research questions posed in our study, nonsummativity informs critical examination of how defining use through one (e.g. number of ED visits) or multiple (e.g. number of ED visits and insurance status) systemic levels (as opposed to evaluating the whole system around patient ED use comprehensively) may impact the conclusions drawn about what constitutes frequent ED use, and how it is to be addressed. Nonsummativity suggests that the whole (e.g., frequent utilization) is greater or different than the sum of one unit (e.g., number of visits in a year) plus another unit (e.g., having a chronic conditions).

Static teleology, is a second construct of systems theory, and suggests that an arrangement of units (e.g., units that come together to construct a definition for frequent utilization) have a certain purpose (e.g., to better identify and prevent unnecessary overuse or misuse of the ED); just as feathers of a bird have a purpose of keeping a bird warm (vonBertalanffy, 1950). Having a systemic perspective when understanding the definition of frequent utilization sheds light on a purpose that likely far exceeds what most have historically attributed to this term. The use of general systems theory and these previously described constructs ground the method and analyses for our systematic review.

Method

This systematic review followed guidelines suggested by the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) statement (Moher, Liberati, Tetzlaff, Altman, & PRISMA, 2009). The search strategy was developed with input and feedback from a research librarian and research team. The search was applied to the following search engines: Medline, PubMed, and Scopus. MeSH terms were used in combination with keywords for the concepts of *frequent use* and *emergency department*. The concept for frequent use included the

terms *frequent use, frequent users, high use, heavy use, overuse, frequent utili*, high utili*, heavy utili*, over-utili*, overutili*, frequent visitors,* and *frequent attenders.* The concept for emergency department included the terms *emergency department, emergency room, emergency care,* and *emergency service.* The search strategy can be found in Appendix A. Due to the large number of searches, and results, the searches were conducted by the researchers over multiple days. Dates and times at which the searches were conducted can be found in Appendix B.

Inclusion criteria included a presence of both frequent use or a synonym and emergency department or a synonym. There were no exclusion criteria at the title review level. Inclusion criteria during the abstract and full text reviews included: (a) English language; (b) peer-reviewed journal; (c) the majority of patients in the study were adults, age 17 years or greater; (d) hospital emergency department setting; (e) all study date and time ranges; (f) a definition of frequent use or a synonym. The reason we did not apply date restrictions is that, according to Cochrane's Handbook (Higgins & Green, 2008), we should not apply date restrictions given that relevant studies on this subject are not relegated to a specific time period.

Exclusion criteria included: (a) vignettes; (b) opinion pieces; and (c) letters to the editor. Articles from other countries were analyzed with those from the U.S., given that studies from other countries frequently cite those from the U.S. and vice versa, and many studies from abroad employ U.S. study definitions of frequent use. Super utilizers of the ED were not included in this study, as the severity of this group's ED utilization (Anderson et al., 2017) has been shown to differ from that of frequent ED users (Byrne et al., 2003; Doupe et al., 2012; Fuda, & Immekus, 2006; Hansagi, Olsson, Sjöberg, Tomson, &Naderi et al., 2012; Zuckerman & Shen, 2004).

Two researchers performed the reviews independently to establish interrater reliability. Each reviewer performed a title and abstract review of the search results for eligibility. For the

title search, reviewers only selected articles that included any of the search terms capturing the concepts of *frequent use* and *emergency department*, as noted previously. Because inclusion and exclusion criteria could not be determined for most articles by reviewing the abstract alone, a full text review was completed for all articles that met inclusion and exclusion criteria at the title level. A title search was then conducted on all reference list titles of articles included following full-text review. Only articles that met title inclusion criteria and had not yet been captured in the search were considered for abstracts and full text review. Articles meeting abstract/full text inclusion criteria were included in the study and then reviewed for exclusion criteria.

Both reviewers extracted definitions for *frequent use* or one of its synonyms independently, using predetermined data fields for extraction. These results were then compared to ensure definitions pulled from each article met inclusion criteria. Following article selection for the review, articles were divided into those that examined frequent users only and those that compared frequent and non-frequent ED users. In order to better analyze the data and theories that informed the definition for frequent utilization, the following three clusters emerged: (a) a general category (which included all patients and diagnoses), (b) target populations (for articles that focused on a specific population), and (c) target diagnosis (for articles that focused on a specific diagnosis.

Using the foundational theory of our systematic review (i.e., systems theory), both reviewers worked to identify the most comprehensive description provided in each definition. Interestingly, most definitions focused on only one unit rather than an arrangement of units. These units include: frequency (e.g. ≥ 4 visits), range (e.g. 3-17), frequency and range (e.g. 5-9 and ≥ 10), most frequent presenters (e.g. 200 patients with the most ED visits), percentile (e.g. 95^{th} percentile of total number of visits across all ED patients), or standard deviation (e.g.

number of visits to the ED greater than the mean plus one standard deviation). Finally, definitions were analyzed by period of time "tested" in relation to utilization for each study (e.g. three months, six months, one year, two years, etc.). See Table 1for this analysis. Theoretical and/or data-informed justification for the operational definition of ED frequent utilization are described in the results section below.

Results

The initial search of the literature yielded 6,928 results (3,635 results in Medline, 3,007 results in PubMed, and 286 results in Scopus) for one reviewer and 7,075 results (3,679 results in Medline, 3,070 results in PubMed, and 326 results in Scopus) for the other reviewer. This discrepancy was due to the fact that searches were conducted several days apart, and the search results fluctuated in PubMed and Scopus databases in particular day-to-day. The title review for all search results yielded 577 and 662 results for the raters, respectively. The search criteria were checked, and found to be the same, indicating that a difference in time of the search was responsible for the discrepancy in number of articles each rater's search yielded. Articles that had not appeared in one or the other rater's search were shared and reviewed by both raters. After removing duplicates, the total unique titles selected were 253 and 256, respectively. The interrater reliability on the title reviews was 98.8%. After joint review of all articles that initially were not agreed upon, the reviewers were able to resolve disagreements through face to face communication and then the raters met 100% agreement on 256 titles.

Of the 256 full text reviews, both raters identified 136 articles that met inclusion and exclusion criteria. There were eight articles for which the two raters had discrepancies, leading to an interrater reliability of 94.1% at the full-text review level. After joint review of the 8 articles for which there was a discrepancy, 137 articles were agreed to meet full text criteria, with inter

rater reliability of 100%. The raters then reviewed all titles in the reference lists of the 137 articles that met full text criteria. Through that process, 73 additional articles met title inclusion criteria, and were agreed upon by both raters. From a full text review of these articles, 25 articles meeting full text criteria, bringing the total number of articles included for analysis to 162. A summary of these results can be found in Figure 1.

Publication dates ranged from 1981 to 2017 (median, 2013 [with just over half (52%) of articles published in or after 2013]). Study designs included retrospective designs using health record data (n=82), cross-sectional (n=17), prospective cohort (n=14), randomized control trial (n=10), systematic review (n=7), qualitative designs (n=7), survey (n=5), mixed method (n=4), observational (n=4), case-control (n=3), and other designs each with only one study, such as pre-post-test single subject design and literature review (n=10). Sample sizes ranged from 19 to 1,272,367 (median=166) for studies of frequent users only, and from 108 to 4,606,622 (median=3,835) for studies comparing frequent and non-frequent users.

Included articles represented findings from many geographic areas (see Table 2). The majority of studies were from North America (United States, n = 77 and Canada, n=22). The remainder included thirty-four from Europe, eleven each from Oceania and Asia, five from multiple/many countries, two from the Middle East, and one from South America.

To calculate age, weighted averages were calculated for all studies reporting total sample size and mean age (See Table 2). The weighted average age for studies examining frequent users only was 51.2 years. The weighted average ages for studies examining both frequent users and non-frequent users were 44.8 and 38.2, respectively, indicating that across included studies frequent users were slightly older than non-frequent users.

Women accounted for a slightly higher proportion of frequent and non-frequent users than men (See Table 2). Among studies of frequent users only, forty-eight percent of patient participants were men and fifty-two percent were women. Among studies comparing frequent and non-frequent users, fifty-three percent of the total study population were women. Five percent of the total study population was comprised of frequent user women, as opposed to frequent user men (3%), non-frequent user women (50%), and non-frequent men (42%).

Few studies of frequent users (only), or those comparing frequent and non-frequent users, had complete racial demographic data (See Table 2). The majority of studies examining frequent users only and frequent user and non-frequent users were from the United States (90% and 94%, respectively). In comparison to U.S. census bureau population estimates (2016), some racial groups were under- or overrepresented among studies of frequent users only. Compared to 2016 U.S. Census estimates, white non-Hispanic individuals comprise (39%) of the study population, while Black (30%) and Latino (25%) individuals comprise a higher portion than are in the U.S. population. Studies comparing frequent and non-frequent users' racial groups had more nuanced racial demographic composition. For example, the proportion of Black (15%), and Latino (12%) individuals in these studies closely mirrors U.S. population estimates, however White, non-Latinos (73%) are overrepresented, and other groups such as Asian (1%), Multiracial (0%), and Native American (0%) are underrepresented in comparison to census estimates (U.S. Census Bureau, 2016). Studies were not included in the calculation of demographic information if they did not report a given demographic (e.g. age, gender, race) or study population size, or the sample sizes for subpopulations reported for a given demographic variable did not sum the total population size. Out of the 162 articles, 84 did not include age, 87 did not include gender, and 119 did not include racial demographics.

Definitions of frequent utilization and its synonyms varied, but could be divided into six distinct typologies, including: frequency (e.g. ≥ 4 visits; n=141), range (e.g. 3-17; n=9), frequency and range (e.g. 5-9 and ≥ 10; n=4), most frequent presenters (e.g. 200 patients with the most ED visits; n=4), percentile (e.g. 95th percentile of total number of visits across all ED patients; n=3), and standard deviation (e.g. number of visits to the ED greater than the mean plus one standard deviation; n=1). The time periods that studies used to define frequent utilization ranged from 1 month to 2 years (mean=11.9 months, median=12 months).

Definition and Operationalization

Justifications given by authors for the definitions they selected included citation of previous literature without further justification, justification (such as "this allowed us to target the sickest patients" in the literature) with no citation, justification with citation (such as, "this is a validated definition," or "ensures no patients making chance encounters will be included in the group"), no citation or justification ("none given"), stating that there is no standard definition, stating that it is a common definition and citing literature, or basing the definition on the data or original empirical work (see Table 1). Overall, the largest proportion of all articles (n=73; 45.1%) provided no justification for the definition provided in the study, including no rationale nor citation to support the definition they used. Just over twelve-percent (n=20) of articles provided a citation(s), but no rationale or explanation for their choice of definition beyond this. A proportion of articles (n=17; 10.5%) provided an explanation for their choice of definition that was not grounded in theory, literature, or data. These articles provided explanations for their choice of definition (e.g., it is the current definition used at the hospital the study is taking place at; it might reflect how clinicians prioritize patient needs; errs on the side of identifying outliers) but do not provide an empirical justification for doing so. Nearly fourteen percent (n=22) of

articles justified the use of a definition by stating that the definition was a common definition used in the literature; these articles usually cited literature when doing so. Likewise, just over six percent (n=10) of articles provided a unique explanation accompanied by citations. Articles justifying their definition of frequent ED use by stating that there is no standard definition made up just under two percent (n=3) of articles. Finally, there were several (n=4; 2.5%) systematic reviews, which provided information regarding the varying ways that frequent ED use was defined in the literature but did not explore justifications for these definitions. Out of 162, just over six percent (n=10) of the articles provided a justification based on data analysis or empirical research, and two percent (n=3) used a validated definition, accompanied by a citation

In Table 1, the middle column contains the three most commonly used definitions for each of the three categories (i.e., general, targeted population, and targeted diagnosis), in descending order from most to least commonly used. Definitions were only included in the table if they were one of the top three most commonly used definitions, and also were used in two or more articles. Superscript citations in the definition column indicate which articles used the given definition. In Table 1, the far-right column contains the three most commonly used justifications for each of the definitions used. Justifications were also only included in the table if they were one of the top three most commonly used justifications, and also were used in two or more articles. Superscript citations were used to indicate articles used to define or justify frequent utilization. These superscripts can be found in the reference list with corresponding references.

General. Out of one-hundred and one articles that met the general category definition (see Methods), the most common definition of frequent utilization found in articles about the general ED population was: four or more visits in one year (n=26; 25.7%). The most common

justification for this definition was actually no justification (n=12; 46.2%); neither an explanation nor citation to support the definition was used. The second most common justification was to state that this was a common definition found in the literature, followed by citations (n=9; 34.6%). Articles using this justification cited eighteen unique articles to support this rationale. The third most common justifications were "cited literature without explanation" and "based on study data" (n=2; 7.6% per justification). The former justification means that these articles cited literature immediately following the description of the definition of frequent use that they chose, but provided no other explanation of their choice, while the latter used some analysis of their study data to choose this definition.

The second most common definition for frequent utilization among articles about the general ED population was five or more visits in one year (n=15; 14.9%). Four articles in the general ED population category used five or more visits in one year as the definition of frequent utilization but did not provide any citation or explanation/rationale to justify their use of this definition (26.7%). Three articles using the definition of five or more visits in one year provided the explanation that this is the most common definition found in the literature (20%) and provided three citations as part of their justification for its use. The third most common justifications were "cited literature without explanation" and "validated definition (n=2; 13.3% per justification)

The third most common definition for frequent utilization among articles about the general ED population was three or more visits in one year (n=8; 7.9%). Three justifications were used by two articles per justification to support this definition (n=2; 25%). These included no citation or explanation, citation of the literature, and unique definitions not based on literature

or data (i.e. “reflects a pattern of dependence on the ED as a source of care,” and, “corresponds to upper 10% of use”).

Providing no explanation or citation is the most common justification given for each of the three most common definitions used in general articles (for three or more visits in one year this justification is tied for the top spot with two others). Citation of the literature without further explanation or rationale for this choice was also a common justification used for all three of the most common definitions. The justification that the definition was a commonly used one was employed as the second most common definition for two of the three definitions.

Targeted population. Some researchers chose to conduct their study at the unit level (i.e., focused on a targeted population, such as: homeless, geriatric, low income and uninsured, Medicaid, Medicare, prisoner, ambulance transported non-emergency, and veteran populations). Targeted populations included in the articles varied, including general (all diagnoses, all populations; n=105), geriatric (n=5), homeless (n=4), Medicaid enrolled (n=2), veterans (n=2), Medicare enrolled (n=1), low income and uninsured (n=1), prisoners with HIV on antiretroviral therapy (n=1), patients transported to the ED with non-urgent conditions (n=1), and adverse childhood experiences and health locus of control (n=1).

For studies focused on targeted populations (n=18), two definitions of frequent utilization were used by two or more articles included in our study. The most common of these was four or more visits in one year (n=8; 44.4%). Four articles (50%) using this definition provided no explanation or citations to justify use of this definition. Three articles provided the explanation that this is a common definition found in the literature (37.5%) and cited six articles as support. The other definition for frequent utilization used in target population studies was two or more

visits in one year (n=3; 16.7%), yet no justification was provided for this definition by any of the articles employing it.

Targeted diagnosis. As with the targeted population category, some researchers chose to conduct their study at a unit level with targeted diagnoses (n=43). Articles that were grouped into the targeted diagnoses category focused on specific patient populations including, heart failure, asthma, chronic diseases, community-onset monomicrobial enterobacteriaceae bacteremia, COPD, mental health and substance abuse, migraines, adverse childhood experiences and health locus of control, sickle cell disease, systemic lupus type 2 diabetes, and unresolved pain. Two definitions were used with equal frequency among articles focused on targeted diagnoses. These included: (a) three or more visits in one year (n=8; 18.6%); and (b) five or more visits in one year (n=8; 18.6%). A third definition—four or more visits in one year—was used by six articles (14%). Citation of the literature without further explanation (n=3; 37.5%) was the most common justification given for the definition of three or more visits in one year, followed by no citation or explanation (n=2; 25%) as the second most common justification for this definition. No other justifications for this definition were used by two or more articles. The only justification for five or more visits in one year provided by two or more articles was none—no citation or explanation (n=6; 75%). The most common justification for four or more visits in one year was none—no citation or explanation (n=3; 50%)—followed by the justification that this is the most common definition (n=2; 33.3%). Three articles were cited to support the justification that the definition of four or more visits in one year is the most common definition of frequent ED use.

Empirically-driven results. Instead of focusing on a number of visits (only), a few articles (n=4, 2.5%) attempted to use data analysis to define frequent users by constructing empirical means by which to categorize ED users based on patient characteristics, rather than

allowing a particular number of visits to either guide their analysis or define frequent ED use outright. One of these studies developed a definition of frequent ED use by comparing differences in the observed frequency distribution of use with that of a theoretical frequency distribution (Locker, Baston, Mason, & Nicholl, 2007). This study ultimately concluded that there is a group of patients that present to the ED repeatedly due to non-random events, and that the concept of "frequent user" is legitimate. At the same time, they also asserted that there is no clear cut-off between chance and frequent users when using an expected frequency distribution, as the two distributions theoretically continue to infinity, and thus they asserted that any visit cut-off to define frequent use is arbitrary. Another empirically-driven study used logistical regression models with select patient characteristics viewed by ED visit frequency to establish "breakpoints" use trends (Doupe et al., 2012). Ultimately this study chose a cut-off point based on number of visits to define frequent ED use, even though patient characteristics were found to exist along the continuum of use and overlap across this breakpoint. Since the publication of Doupe and colleagues' (2012) article, only two articles (1.2%) that met criteria for inclusion in this systematic review were found to have used empirically-based methodology to identify frequent ED users (Pereira et al., 2016; Wu, Grannis, Xu, & Finnell, 2016). Pereira and colleagues (2016) presented empirical work at a conference using machine learning models to predict frequent ED use based on patient characteristics, however they used number of visits to define frequent ED use. Wu, Grannis, Xu, and Finnell (2016) developed logistic regression models based on patient characteristics and use to predict ED visits across multiple years. However, in this study they used visit cut-points ranging from 8 to 16 visits over a two-year period to fit their models, meaning that they still chose a visit range to identify frequent users.

Discussion

The articles in this review span four decades of research and employ a variety of definitions of frequent ED utilization primarily focused on the number of ED visits patients make, for the purposes of describing the population and evaluating the success of interventions as measured by a reduction in visits. Overall, the largest proportion of all articles (45.1%) provided no justification, including neither rationale nor citation to support the definition they used. Four or more visits in one year was the most common definition of frequent ED use in both general and targeted population categories, while three or more and five or more visits in one year were the most common for the targeted diagnosis category. Seven of the eight common definitions used in these three article categories had no explanation or citation as the top justification for use of the definition. When justifications were provided, researchers often stated that the selected definition was "common" in the literature and/or then cited literature without further explanation; this was reflected in half of the definitions used across the three categories.

Many of the articles cited in our systematic review provided background discussion on how frequent ED use has been defined in the past, but when providing the definition, they used to operationalize frequent ED use in their studies, they did not explain why they chose that particular definition. In our study, we found that operational definitions of frequent utilization are typically neither theoretically grounded or data informed. As such interventions, research, and policies that rely on definitions from the articles included in our study (particularly those that use level or type of frequent utilization to label patients or determine cutoff for treatment) are concerning at best and detrimental to the healthcare system in the worst case scenario (e.g. such approaches ignore patient needs, health outcomes, social determinants of health, etc.).

Our systematic review also found that since the publication of Doupe and colleagues' (2012) article, only two of the studies that met inclusion criteria for this review (out of 84; 2.4%) and were published in 2013 or after, have used empirically-based methodology to identify frequent ED users (Pereira et al., 2016; Wu, Grannis, Xu, & Finnell, 2016). Although this is progress, these articles still resorted to using a number of ED visits as the way to define ED user groups. While these articles move closer to taking a systems approach to understanding utilization patterns and the patient characteristics and factors associated with it, in the end they still resort to highlighting a particular number of visits as the cutoff for frequent use. This is unhelpful given that patient characteristics, usage patterns, and healthcare needs exist along a continuum (Weber, 2012). Despite evidence of other possibilities, and criticism of the old way of defining ED use based on a number of visits, most researchers continue to use definitions that are nonsummative and that do not allow new information about patients and the context in which they use the ED to be accounted for.

Our systematic review makes several unique contributions to the literature. One of the unique contributions of this review is a clear demonstration of the extent to which the bulk of literature on frequent ED utilizers lacks an empirical foundation for the definition of the problem as its seen and the marker by which outcomes are assessed. There are exceptions to this, as have been noted, however many articles do not provide any justification for their definition, or when they do, may assert that they used the most common definition, rather than one grounded in theory or research. Another contribution of this systematic review is that it underlines the need for empirical understanding of ED utilization that takes into account systemic factors associated with use.

Limitations

While the method and analysis of the literature in this area was thorough, some limitations do exist in relation to this article. For example, it is possible that other databases that were not accessed could have included other unique articles that would have met the research criteria (e.g., CINAHL).

Implications for Future Research

When reflecting on these findings through the lens of general systems theory, it is clear that researchers to this point have largely attempted to define frequent ED use by examining only one unit of the whole system - the number of visits a person makes to the emergency department. Interestingly, despite evidence to the contrary (Mandelberg, Kuhn, & Kohn, 2000), the majority of these researchers also continue to define this use over a period of one year, ignoring the fact that there is evidence that the majority of users cease to visit frequently after one year. This is problematic for a host of reasons already mentioned, not least of which is the well-documented heterogeneity of this group (Weber, 2012). Through a general systems theory lens this would suggest that the conclusion we can draw from this literature is that at one systemic level—a given number of visits—certain patient characteristics are more common. However, we cannot conclude anything about the larger systemic picture of frequent ED use. Future efforts to understand ED use should be based on a systemic lens in which all characteristics and factors associated with the patients using the ED are considered.

A few articles have attempted to create objective thresholds for frequent ED use (Doupe et al., 2012; Locker, Baston, Mason, & Nicholl, 2007). Yet such methods have still ultimately resorted to choosing a numeric threshold or "breakpoint" even though patient characteristics overlapped across these numeric markers (e.g. mental health concerns, patients with many

primary care visits, etc.). This demonstrates that frequent use exists along a continuum, and that mathematical and descriptive (i.e. establishing breakpoints or using a number of ED visits) definitions of frequent ED use are an oversimplification (Weber, 2012). Further, although the literature may suggest that patients are more likely to have certain characteristics given a particular threshold of use, having a certain number of ED visits is not essential to possess those characteristics, and not all patients with such use will (e.g. the presence of such factors as frequent primary care use among non-frequent and frequent users).

Using a mathematical or descriptive numeric definition of frequent use also eschews the fact that many frequent users may be quite sick, and require more healthcare resources overall (Byrne et al., 2003; Chan & Ovens, 2002; Hansagi et al., 2001), making the ED an appropriate context for care. As Weber (2012) points out, "frequent use is only 'too frequent' if the patient could have been better served in another setting or with another approach (p. 33)." This view falls in stark contrast to the rationale for the most commonly cited definition of frequent use—four or more visits in one year—which was originally selected as it was thought that this would help reduce ED overcrowding (Cook et al., 2004; Hunt et al., 2006; Naughton et al., 2010; Sun, Burstin, & Brennan, 2003). This further punctuates the need for a systems approach (vonBertalanffy, 1968) to understanding frequent use, given the clear evidence that looking at only one level of the system that comprises frequent ED use results in us only understanding that level, and not the overall system and factors contributing to frequent ED use. This also denounces the fact that some proportion of this population may be in need of additional or different interventions or resources.

Future researchers should focus on creating a holistic, systemic understanding of the individuals that frequently utilize the ED, and across time. Instead of setting a numeric threshold,

researchers should look to identify distinctive subgroups of patients through consideration of as many systemic factors (e.g. demographics, diagnosis, treatment interventions, medications, disposition, etc.) as possible. "Defining" ED users in this way will support efforts to identify appropriate interventions, not necessarily for the purpose of reducing visits, but for the purpose of improving health outcomes and access to appropriate kinds of care. As suggested by Doupe et al. (2012), one approach that would allow for this is a cluster analysis. A cluster analysis would create cohorts of ED patients based on many characteristics and factors (e.g. diagnosis, interventions received, race, age, etc.). This should be undertaken using a large, heterogeneous dataset, representing many social locations and characteristics so as to be as generalizable as possible in order to support providers in better understanding the systemic factors associated with ED utilization. Such an analysis would also inform the development of interventions and approaches that meet the needs of these unique patient subgroups.

Implications for providers. This review highlights the fact that presently we do not have a definition of frequent ED utilization that grounds our understanding of the phenomenon. In the absence of research that provides a systemic understanding of this phenomenon, it is critical that providers use a systemic lens when interpreting ED utilization. Ways to do this may include considering such factors as diagnosis and symptom severity, social supports, and other biopsychosocial factors when contemplating whether an appropriate goal for a given patient should be to reduce the number of ED visits they make. Better still, each patient's biopsychosocial system of whole health should be considered and rather than asking if they are making too many visits, providers should ask whether they are getting the appropriate care for their needs given all these factors.

Conclusions

This systematic review sought to understand how frequent use of the ED is operationalized in the literature. Informed by general systems theory (vonBertalanffy, 1968), it was of particular interest whether definitions would be operationalized in a manner consistent with: 1) the rule of nonsummativity, acknowledging that many factors or systemic levels of health and factors inform use and 2) static teleology, addressing what purpose the use of a particular definition of frequent utilization serves. The findings suggest that most (97%) articles use only one unit to operationalize frequent ED use (i.e. number of visits to the ED). Moreover, many (45.1%) provide no justification for the definition used in their study, and less than three percent (2.5%) provided empirical evidence for the selection of their criteria. When researchers only focus on the number of visits individuals make to the ED, this naturally informs interventions and studies focused on reducing the number of visits as the measure of success, rather than understanding more about the root cause of use, or how interventions might impact health outcomes.

This review demonstrates the extent to which the bulk of literature on frequent ED utilizers lacks an empirical foundation. There are exceptions to this, as have been noted, however many articles do not provide any justification for their definition, or when they do, may assert that they used the most common definition. This begs the question, "how are we to know that a change in number of ED visits demonstrates progress or improvement for patients?" The findings of this review underline the need for empirical understanding of ED utilization that takes into account systemic factors associated with use. As has been demonstrated previously, frequent ED users are a heterogeneous group, and have been found to have more complex biopsychosocial needs that touch on multiple systemic layers of health and wellbeing (Weber,

2012). Given this knowledge, it is inappropriate to continue to perpetuate the agenda of using a number of visits or a reduction in the number of visits to the ED as an appropriate focus for research, when it ignores the patient and fails to consider whether their biopsychosocial, systemic health needs are being met. Healthcare utilization has systemic implications and using the number of visits to the ED as the sole means of identifying frequent ED users is an oversimplification that leads to a nonsummative conclusion about patients, the systemic factors associated with their ED use, and the biopsychosocial health needs that lead to it.

REFERENCES

Aagaard, J., Aagaard, A., & Buus, N. (2014). Predictors of frequent visits to a psychiatric emergency room: A large-scale register study combined with a small-scale interview study. International *Journal of Nursing Studies, 51*, 1003-1013. doi: 10.1016/j.ijnurstu.2013.11.002[1]

Acosta, A. M., & Lima, Maria Alice Dias da Silva. (2015). Frequent users of emergency services: Associated factors and reasons for seeking care. *Revista Latino-Americana De Enfermagem, 23*, 337-344. doi:10.1590/0104-1169.0072.2560[104]

Aisiku, I. P., Smith, W. R., McClish, D. K., Levenson, J. L., Penberthy, L. T., Roseff, S. D., ... & Roberts, J. D. (2009). Comparisons of high versus low emergency department utilizers in sickle cell disease. *Annals of Emergency Medicine, 53*, 587-593. doi: 10.1016/j.annemergmed.2008.07.050[2]

Alghanim, S. A., & Alomar, B. A. (2015). Frequent use of emergency departments in Saudi public hospitals: Implications for primary health care services. *Asia-Pacific Journal of Public Health, 27*, NP2521-NP2530. doi:10.1177/1010539511431603[3]

Althaus, F., Paroz, S., Hugli, O., Ghali, W. A., Daeppen, J., Peytremann-Bridevaux, I., & Bodenmann, P. (2011). Effectiveness of interventions targeting frequent users of emergency departments: A systematic review. *Annals of Emergency Medicine, 58*, 41-52.e42. doi:10.1016/j.annemergmed.2011.03.007[4]

Anderson, D., Patch, E., Oxandale, B., Kincade, A., Gamber, A., & Ohm, R. (2017). Nursing student coaches for emergency department super utilizers. *Journal of Nursing Education, 56*, 27-30. doi:10.3928/01484834-20161219-06

Andrén, K. G. (1988). A study of the relationship between social network, perceived ill health and utilization of emergency care: A case-control study. *Scandinavian Journal of Social Medicine, 16,* 87-93. doi: 10.1177/140349488801600205[5]

Andrén, K. G., & Rosenqvist, U. (1987). An ecological study of the relationship between risk indicators for social disintegration and use of a somatic emergency department. *Social Science & Medicine, 25*(10), 1121-1127.[6]

Andrén, K. G., & Rosenqvist, U. (1987). Heavy users of an emergency department—a two year follow-up study. *Social Science & Medicine, 25*, 825-831. doi: 10.1016/0277-9536(87)90040-2[7]

Andrén, K. G., & Rosenqvist, U. (1985). Heavy users of an emergency department: Psycho-social and medical characteristics, other health care contacts and the effect of a hospital social worker intervention. *Social Science & Medicine, 21*, 761-770. doi:10.1016/0277-9536(85)90124-8[8]

Baggio, S., Iglesias, K., Hugli, O., Burnand, B., Ruggeri, O., Wasserfallen, J. B., ... & Daeppen, J. B. (2017). Associations between perceived discrimination and health status among frequent emergency department users. *European Journal of Emergency Medicine, 24*, 136-141. doi: 10.1097/MEJ.0000000000000311[9]

Bernstein, S. L. (2006). Frequent emergency department visitors: The end of inappropriateness. *Annals of Emergency Medicine, 48,* 18-20. doi: 10.1016/j.annemergmed.2006.03.033[12]

Bertoli-Avella, A. M., Haagsma, J. A., Van Tiel, S., Erasmus, V., Polinder, S., Van Beeck, E., ... & Rood, P. P. (2017). Frequent users of the emergency department services in the largest academic hospital in the Netherlands: A 5-year report. *European Journal of Emergency Medicine, 24*, 130-135. doi: 10.1097/MEJ.0000000000000314[103]

Bieler, G., Paroz, S., Faouzi, M., Trueb, L., Vaucher, P., Althaus, F., ... & Bodenmann, P. (2012). Social and medical vulnerability factors of emergency department frequent users in a universal health insurance system. *Academic Emergency Medicine, 19*, 63-68. doi: 10.1111/j.1553-2712.2011.01246.x.[13]

Birmingham, L. E., Cochran, T., Frey, J. A., Stiffler, K. A., & Wilber, S. T. (2017). Emergency department use and barriers to wellness: A survey of emergency department frequent users. *BMC Emergency Medicine, 17*, 16. doi: 10.1186/s12873-017-0126-5.[101]

Bodenmann, P., Baggio, S., Iglesias, K., Althaus, F., Velonaki, V., Stucki, S., . . . Daeppen, J. (2015). Characterizing the vulnerability of frequent emergency department users by applying a conceptual framework: A controlled, cross-sectional study. *International Journal for Equity in Health*, *14*, 146. doi: 10.1186/s12939-015-0277-5[112]

Bodenmann, P., Velonaki, V., Griffin, J. L., Baggio, S., Iglesias, K., Moschetti, K., . . . Daeppen, J. (2017). Case management may reduce emergency department frequent use in a universal health coverage system: A randomized controlled trial. *Journal of General Internal Medicine, 32*, 508-515. doi:10.1007/s11606-016-3789-9[116]

Bodenmann, P., Velonaki, V., Ruggeri, O., Hugli, O., Burnand, B., Wasserfallen, J., . . . Daeppen, J. (2014). Case management for frequent users of the emergency department: Study protocol of a randomized controlled trial. *BMC Health Services Research, 14*, 264-264. doi:10.1186/1472-6963-14-264[113]

Boh, C., Li, H., Finkelstein, E., Haaland, B., Xin, X., Yap, S., . . . Hauswald, M. (2015). Factors contributing to inappropriate visits of frequent attenders and their economic effects at an emergency department in Singapore. *Academic Emergency Medicine*, 22, 1025-1033. doi:10.1111/acem.12738[14]

Brennan, J. J., Chan, T. C., Hsia, R. Y., Wilson, M. P., & Castillo, E. M. (2014). Emergency department utilization among frequent users with psychiatric visits. *Academic Emergency Medicine, 21*, 1015-1022. doi: 10.1111/acem.12453.[15]

Brunero, S., Fairbrother, G., Lee, S., & Davis, M. (2007). Clinical characteristics of people with mental health problems who frequently attend an Australian emergency department. *Australian Health Review, 31*(3), 462-470.[16]

Buhumaid R, Riley J, Blanchard J. (2012). A comparison of frequent and infrequent emergency department users among patients with a psychiatric diagnosis. *Academic Emergency Medicine, 19,* S357.[17]

Buhumaid, R., Riley, J., Sattarian, M., Bregman, B., & Blanchard, J. (2015). Characteristics of frequent users of the emergency department with psychiatric conditions. *Journal of Health Care for the Poor and Underserved, 26*, 941-950. doi: 10.1353/hpu.2015.0079[18]

Byrne, M., Murphy, A. W., Plunkett, P. K., McGee, H. M., Murray, A., & Bury, G. (2003). Frequent attenders to an emergency department: A study of primary health care use, medical profile, and psychosocial characteristics. *Annals of Emergency Medicine, 41*, 309-318. doi:10.1067/mem.2003.68[19]

Capp, R., Rosenthal, M. S., Desai, M. M., Kelley, L., Borgstrom, C., Cobbs-Lomax, D. L., ... & Spatz, E. S. (2013). Characteristics of Medicaid enrollees with frequent ED use. *American Journal of Emergency Medicine, 31*, 1333-1337. doi: 10.1016/j.ajem.2013.05.050[105]

Castner, J., Wu, Y. B., Mehrok, N., Gadre, A., & Hewner, S. (2015). Frequent emergency department utilization and behavioral health diagnoses. *Nursing Research, 64*, 3-12. doi:10.1097/NNR.0000000000000065[108]

Chan, B. T., & Ovens, H. J. (2002). Frequent users of emergency departments. Do they also use family physicians' services?. *Canadian Family Physician, 48*(10), 1654-1660.[10]

Chang, G., Weiss, A. P., Orav, E. J., & Rauch, S. L. (2014). Predictors of frequent emergency department use among patients with psychiatric illness. *General Hospital Psychiatry, 36*, 716-720. doi: 10.1016/j.genhosppsych.2014.09.010[21]

Chaput, Y. J., & Lebel, M. J. (2007). Demographic and clinical profiles of patients who make multiple visits to psychiatric emergency services. *Psychiatric Services, 58*, 335-341. doi: 10.1176/ps.2007.58.3.335[22]

Colligan, E. M., Pines, J. M., Colantuoni, E., Howell, B., & Wolff, J. L. (2016). Risk factors for persistent frequent emergency department use in Medicare beneficiaries. *Annals of Emergency Medicine, 67*, 721-729. 10.1016/j.annemergmed.2016.01.033.[23]

Cook, L. J., Knight, S., Junkins, E. P., Mann, N. C., Dean, J. M., & Olson, L. M. (2004). Repeat patients to the emergency department in a statewide database. *Academic Emergency Medicine, 11*, 256-263. doi: 10.1111/j.1553-2712.2004.tb02206.x[24]

Dent, A., Hunter, G., & Webster, A. P. (2010). The impact of frequent attenders on a UK emergency department. *European Journal of Emergency Medicine, 17*, 332-336. doi:10.1097/MEJ.0b013e328335623d[4]

Dent, A. W., Phillips, G. A., Chenhall, A. J., & McGregor, L. R. (2003). The heaviest repeat users of an inner city emergency department are not general practice patients. *Emergency Medicine Australasia, 15*, 322-329. doi: 10.1046/j.1442-2026.2003.00470.x[25]

Doran, K. M., Colucci, A. C., Wall, S. P., Williams, N. D., Hessler, R. A., Goldfrank, L. R., & Raven, M. C. (2014). Reasons for emergency department use: Do frequent users differ? *The American Journal of Managed Care, 20*(11), e506-14.[26]

Doupe, M. B., Palatnick, W., Day, S., Chateau, D., Soodeen, R. A., Burchill, C., & Derksen, S. (2012). Frequent users of emergency departments: Developing standard definitions and defining prominent risk factors. *Annals of Emergency Medicine, 60*, 24-32. doi: 10.1016/j.annemergmed.2011.11.036

Edgren, G., Anderson, J., Dolk, A., Torgerson, J., Nyberg, S., Skau, T., . . . Öhlen, G. (2016). A case management intervention targeted to reduce healthcare consumption for frequent emergency department visitors: Results from an adaptive randomized trial. *European Journal of Emergency Medicine, 23*, 344-350. doi:10.1097/MEJ.0000000000000280[27]

Fuda, K. K., & Immekus, R. (2006). Frequent users of Massachusetts emergency departments: A statewide analysis. *Annals of Emergency Medicine, 48*, 16-e1. doi: 10.1016/j.annemergmed.2006.03.001[28]

Griffin et al., 2016. Characteristics and predictors of mortality among frequent users of an Emergency Department in Switzerland. *European Journal of Emergency Medicine*. Advance online publication. doi: 10.1097/MEJ.0000000000000425[111]

Grover, C. A., Close, R. J., Villarreal, K., & Goldman, L. M. (2010). Emergency department frequent user: Pilot study of intensive case management to reduce visits and computed tomography. *The Western Journal of Emergency Medicine, 11*(4), 336-343.[29]

Grover, C. A., Crawford, E., & Close, R. J. H. (2016). The efficacy of case management on emergency department frequent users: An eight-year observational study. *The Journal of Emergency Medicine, 51*, 595-604. doi:10.1016/j.jemermed.2016.06.002[30]

Hansagi, H., Allebeck, P., Edhag, O., & Magnusson, G. (1990). Frequency of emergency department attendances as a predictor of mortality: Nine-year follow-up of a population-based cohort. *Journal of Public Health Medicine, 12*(1), 39.[31]

Hansagi, H., Edhag, O., & Allebeck, P. (1991). High consumers of health care in emergency units: how to improve their quality of care. *International Journal for Quality in Health Care, 3*, 51-62. doi: 10.1093/intqhc/3.1.51[32]

Hansagi, H., Olsson, M., Hussain, A., & Öhlén, G. (2008). Is information sharing between the emergency department and primary care useful to the care of frequent emergency department users? European Journal of Emergency Medicine, 15, 34-39. doi:10.1097/MEJ.0b013e3282aa4115[106]

Hansagi, H., Olsson, M., Sjoberg, S., Tomson, Y., & Goransson, S. (2001). Frequent use of the hospital emergency department is indicative of high use of other health care services. *Annals of Emergency Medicine, 37*, 561–7. doi: 10.1067/mem.2001.111762[33]

Hansen, T. E., & Elliott, K. D. (1993). Frequent psychiatric visitors to a Veterans Affairs medical center emergency care unit. Psychiatric Services, 44, 372-375. doi: 10.1176/ps.44.4.372[120]

Hardie, T. L., Polek, C., Wheeler, E., McCamant, K., Dixson, M., Gailey, R., & Lafrak, K. (2015). Characterising emergency department high-frequency users in a rural hospital. *Emergency Medicine Journal, 32*, 21-25. doi:10.1136/emermed-2013-202369[35]

Hasegawa, K., Tsugawa, Y., Brown, D. F., & Camargo Jr, C. A. (2014). A population-based study of adults who frequently visit the emergency department for acute asthma. California and Florida, 2009–2010. *Annals of the American Thoracic Society, 11*, 158-166. doi: 10.1513/AnnalsATS.201306-166OC.[34]

Helliwell, P. E., Hider, P. N., & Ardagh, M. W. (2001). Frequent attenders at Christchurch Hospital's emergency department. *The New Zealand Medical Journal, 114*(1129), 160.[36]

Higgins, J. P., & Green, S. (Eds.). (2011). *Cochrane handbook for systematic reviews of interventions* (Vol. 4). John Wiley & Sons.

Huang, J. A., Lai, C. S., Tsai, W. C., Weng, R. H., Hu, W. H., & Yang, D. Y. (2004). Determining factors of patient satisfaction for frequent users of emergency services in a medical center. *Journal-Chinese Medical Association, 67*(8), 403-410.[38]

Huang, J. A., Tsai, W. C., Chen, Y. C., Hu, W. H., & Yang, D. Y. (2003). Factors associated with frequent use of emergency services in a medical center. *Journal-Formosan Medical Association, 102*(4), 222-228.[39]

Hudon, C., Sanche, S., & Haggerty, J. L. (2016). Personal characteristics and experience of primary care predicting frequent use of emergency department: A prospective cohort study. *PloS one, 11*, e0157489. doi: 10.1371/journal.pone.0157489 [40]

Hunt, K.A., Weber, E.J., Showstack, J.A., Colby, D.C., & Callaham, M.L. (2006). Characteristics of frequent users of emergency departments. *Annals of Emergency Medicine, 48*, 1–8. doi: 10.1016/j.annemergmed.2005.12.030[41]

Huynh, C., Ferland, F., Blanchette-Martin, N., Ménard, J. M., & Fleury, M. J. (2016). Factors influencing the frequency of emergency department utilization by individuals with substance use disorders. *Psychiatric Quarterly, 87*, 713-728. doi: 10.1007/s11126-016-9422-6[42]

Jacob, R., Wong, M. L., Hayhurst, C., Watson, P., & Morrison, C. (2016). Designing services for frequent attenders to the emergency department: A characterization of this population to inform service design. *Clinical Medicine, 16*, 325-329. doi:10.7861/clinmedicine.16-4-325[114]

Jelinek, G., Gibson, N., Jiwa, M., & Lynch, A. (2008). Frequent attenders at emergency departments: A linked-data population study of adult patients. *Medical Journal of Australia, 189*(10), 552-556.[117]

Kahan, D., Leszcz, M., O'Campo, P., Hwang, S. W., Wasylenki, D. A., Kurdyak, P., ... & Stergiopoulos, V. (2016). Integrating care for frequent users of emergency departments: Implementation evaluation of a brief multi-organizational intensive case management intervention. *BMC Health Services Research, 16*, 156. doi: 10.1186/s12913-016-14075[43]

Kahan, D., Poremski, D., Wise-Harris, D., Pauly, D., Leszcz, M., Wasylenki, D., & Stergiopoulos, V. (2016). Perceived case management needs and service preferences of frequent emergency department users: Lessons learned in a large urban centre. PloS one, 11, e0168782. doi: 10.1371/journal.pone.0168782[44]

Kennedy, D., & Ardagh, M. (2004). Frequent attenders at Christchurch hospital's emergency department: A 4-year study of attendance patterns. *The New Zealand Medical Journal, 117*(1193), U871.[46]

Kirby, S. E., Dennis, S. M., Jayasinghe, U. W., & Harris, M. F. (2011). Frequent emergency attenders: Is there a better way? *Australian Health Review, 35*, 462. doi:10.1071/AH10964[102]

Kne, T., Young, R., & Spillane, L. (1998). Frequent ED users: Patterns of use over time. *American Journal of Emergency Medicine, 16*, 648-652. doi:10.1016/S0735-6757(98)90166-8

Kushel, M. B., Perry, S., Bangsberg, D., Clark, R., & Moss, A. R. (2002). Emergency department use among the homeless and marginally housed: Results from a community-based study. *American Journal of Public Health, 92*(5), 778-784.[99]

Kwan, B. M., Rockwood, A., Bandle, B., Fernald, D., Hamer, M. K., & Capp, R. (2017). Community health workers: Addressing client objectives among frequent emergency department users. *Journal of Public Health Management and Practice*. Advance online publication. doi:10.1097/PHH.0000000000000540[47]

LaCalle, E., & Rabin, E. (2010). Frequent users of emergency departments: the myths, the data, and the policy implications. *Annals of Emergency Medicine, 56*, 42–48. doi:10.1016/j.annemergmed.2010.01.032[48]

LaCalle, E. J., Rabin, E. J., & Genes, N. G. (2013). High-frequency users of emergency department care. *The Journal of Emergency Medicine, 44*, 1167-1173. doi:10.1016/j.jemermed.2012.11.042[49]

Lee, C. H., Chu, F. Y., Hsieh, C. C., Hong, M. Y., Chi, C. H., Ko, W. C., & Lee, C. C. (2017). A simple scoring algorithm predicting extended-spectrum β-lactamase producers in adults with community-onset monomicrobial Enterobacteriaceae bacteremia: Matters of frequent emergency department users. *Medicine, 96*, e6648. doi: 10.1097/MD.0000000000006648.[50]

Legramante, J. M., Marciano, L., Lucaroni, F., Gilardi, F., Caredda, E., Pesaresi, A., ... & Di Lecce, V. N. (2016). Frequent use of emergency departments by the elderly population when continuing care is not well established. *PloS one, 11*, e0165939. doi: 10.1371/journal.pone.0165939 [51]

Leporatti, L., Ameri, M., Trinchero, C., Orcamo, P., & Montefiori, M. (2016). Targeting frequent users of emergency departments: Prominent risk factors and policy implications. *Health Policy, 120*, 462-470. doi:10.1016/j.healthpol.2016.03.005[52]

Locker, T. E., Baston, S., Mason, S. M., & Nicholl, J. (2007). Defining frequent use of an urban emergency department. *Emergency Medicine Journal, 24*, 398-401. doi: 10.1136/emj.2006.043844[53]

Lucas, R. H., & Sanford, S. M. (1998). An analysis of frequent users of emergency care at an urban university hospital. *Annals of Emergency Medicine, 32*, 563-568. doi:10.1016/S0196-0644(98)70033-2.[54]

Malone, R. E. (1995). Heavy users of emergency services: Social construction of a policy problem. *Social Science & Medicine, 40*, 469–477. doi: 10.1016/0277-9536(94)E0116-A[56]

Mandelberg, J. H., Kuhn, R. E., & Kohn, M. A. (2000). Epidemiologic analysis of an urban, public emergency department's frequent users. *Academic Emergency Medicine, 7*, 637-646. doi: 10.1111/j.1553-2712.2000.tb02037.x[57]

Mehl-Madrona, L. E. (2008). Prevalence of psychiatric diagnoses among frequent users of rural emergency medical services. *Canadian Journal of Rural Medicine*, *13*(1), 22.

Meyer, J. P., Qiu, J., Chen, N. E., Larkin, G. L., & Altice, F. L. (2013). Frequent emergency department use among released prisoners with human immunodeficiency virus: Characterization including a novel multimorbidity index. *Academic Emergency Medicine, 20*, 79-88. doi: 10.1111/acem.12054[124]

Minassian, A., Vilke, G. M., & Wilson, M. P. (2013). Frequent emergency department visits are more prevalent in psychiatric, alcohol abuse, and dual diagnosis conditions than in

chronic viral illnesses such as hepatitis and human immunodeficiency virus. *The Journal of Emergency Medicine, 45*, 520-525. doi:10.1016/j.jemermed.2013.05.007[59]

Mitchell, M. S., León, C. L., Byrne, T. H., Lin, W. C., & Bharel, M. (2017). Cost of health care utilization among homeless frequent emergency department users. *Psychological Services, 14*, 193. doi: 10.1037/ser0000113.[60]

Moe, J., Bailey, A. L., Oland, R., Levesque, L., & Murray, H. (2013). Defining, quantifying, and characterizing adult frequent users of a suburban Canadian emergency department. *Canadian Journal of Emergency Medicine, 15*, 214-226. doi:10.2310/8000.2013.130936[119]

Moe, J., Kirkland, S., Ospina, M. B., Campbell, S., Long, R., Davidson, A., . . . Rowe, B. H. (2016). Mortality, admission rates and outpatient use among frequent users of emergency departments: A systematic review. *Emergency Medicine Journal, 33*, 230-236. doi:10.1136/emermed-2014-204496[61]

Moe, J., Kirkland, S. W., Rawe, E., Ospina, M. B., Vandermeer, B., Campbell, S., . . . Gratton, M. C. (2017). Effectiveness of interventions to decrease emergency department visits by adult frequent users: A systematic review. *Academic Emergency Medicine, 24*, 40-52. doi:10.1111/acem.13060[62]

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS medicine, 6*, e1000097. doi: 10.1371/journal.pmed.1000097

Moore, L., Deehan, A., Seed, P., & Jones, R. (2009). Characteristics of frequent attenders in an emergency department: Analysis of 1-year attendance data. *Emergency Medicine Journal, 26*, 263-267. doi:10.1136/emj.2008.059428[63]

Moore, G., Gerdtz, M., Manias, E., Hepworth, G., & Dent, A. (2007). Socio-demographic and clinical characteristics of re-presentation to an Australian inner-city emergency department: Implications for service delivery. *BMC Public Health, 7*, 320. doi: 10.1186/1471-2458-7-320

Naderi S., Barnett, B. Hoffman, R.S. Dalipi, R. Houdek, L. Alagappan, K. Silverman, R. (2012). Factors associated with failure to follow-up at a medical clinic after an ED visit. *The American Journal of Emergency Medicine, 30*, 347-351. doi: 10.1016/j.ajem.2010.11.034

Naughton, C., Drennan, J., Treacy, P., Fealy, G., Kilkenny, M., Johnson, F., & Butler, M. (2010). The role of health and non-health-related factors in repeat emergency department visits in an elderly urban population. *Emergency Medicine Journal, 27*, 683-687. doi: 10.1136/emj.2009.077917

Nejtek, V. A., Aryal, S., Talari, D., Wang, H., & O'Neill, L. (2017). A pilot mobile integrated healthcare program for frequent utilizers of emergency department services. *The American Journal of Emergency Medicine, 35,* 1792-1705. doi: 10.1016/j.ajem.2017.04.061[119]

Neufeld, E., Viau, K. A., Hirdes, J. P., & Warry, W. (2016). Predictors of frequent emergency department visits among rural older adults in Ontario using the Resident Assessment Instrument-Home Care. *Australian Journal of Rural Health, 24*, 115-122. doi: 10.1111/ajr.12213[64]

Nossel, I. R., Lee, R. J., Isaacs, A., Herman, D. B., Marcus, S. M., & Essock, S. M. (2016). Use of peer staff in a critical time intervention for frequent users of a psychiatric emergency room. *Psychiatric Services, 67*, 479-481.

Okin, R. L., Boccellari, A., Azocar, F., Shumway, M., O'Brien, K., Gelb, A., . . . Wachsmuth, C. (2000). The effects of clinical case management on hospital service use among ED frequent users. *The American Journal of Emergency Medicine, 18*, 603-608. doi:10.1053/ajem.2000.9292[110]

Okuyemi, K. S., & Frey, B. (2001). Describing and predicting frequent users of an emergency department. *Journal of the Association for Academic Minority Physicians, 12*(1-2), 119-123.[67]

Oliveira, A. (2008). Hyperusers and emergency. *Acta Medica Portuguesa, 21*(6), 553-8.[66]

Ondler, C., Hegde, G. G., & Carlson, J. N. (2014). Resource utilization and health care charges associated with the most frequent ED users. *The American Journal of Emergency Medicine, 32*, 1215. doi:10.1016/j.ajem.2014.07.013[67]

Palmer E, Leblanc-Duchin D, Murray J, Atkinson P. Emergency department use: Is frequent use associated with a lack of primary care provider? *Canadian Family Physician, 60*(4), e223–e229.[68]

Panopalis, P., Gillis, J. Z., Yazdany, J., Trupin, L., Hersh, A., Julian, L., ... & Yelin, E. (2010). Frequent use of the emergency department among persons with systemic lupus erythematosus. *Arthritis Care & Research, 62*, 401-408. doi: 10.1002/acr.20107[69]

Paul, P., Heng, B. H., Seow, E., Molina, J., & Tay, S. Y. (2010). Predictors of frequent attenders of emergency department at an acute general hospital in Singapore. *Emergency Medicine Journal, 27*, 843-848. doi: 10.1136/emj.2009.079160[70]

Pereira, M., Singh, V., Hon, C., McKelvey, T., Sushmita, S., & De Cock, M. (2016). Predicting future frequent users of emergency departments in California state. Paper presented at *ACM International Conference,* 603-610. doi:10.1145/2975167.2985845

Pillow, M. T., Doctor, S., Brown, S., Carter, K., & Mulliken, R. (2013). An emergency department-initiated, web-based, multidisciplinary approach to decreasing emergency department visits by the top frequent visitors using patient care plans. *The Journal of Emergency Medicine, 44*, 853-860. doi:10.1016/j.jemermed.2012.08.020.[71]

Pines, J. M., & Buford, K. (2006). Predictors of frequent emergency department utilization in Southeastern Pennsylvania. *Journal of Asthma, 43*, 219-223. doi: 10.1080/02770900600567015[72]

Poremski, D., Harris, D. W., Kahan, D., Pauly, D., Leszcz, M., O'Campo, P., ... & Stergiopoulos, V. (2016). Improving continuity of care for frequent users of emergency departments: service user and provider perspectives. *General Hospital Psychiatry, 40*, 55-59. doi: 10.1016/j.genhosppsych.2016.01.004[73]

Poremski, D., Kunjithapatham, G., Koh, D., Lim, X. Y., Alexander, M., & Lee, C. (2016). Lost keys: Understanding service providers' impressions of frequent visitors to psychiatric emergency services in Singapore. *Psychiatric Services, 68*, 390-395. doi: 10.1176/appi.ps.201600165[74]

Purdie, F. R., Honigman, B., & Rosen, P. (1981). The chronic emergency department patient. *Annals of Emergency Medicine, 10*(6), 298-301.[107]

Ramasubbu, B., Donnelly, A., & Moughty, A. (2016). Profile of frequent attenders to a Dublin inner city emergency department. *Irish Medical Journal, 109*, 389.[75]

Rask, K. J., Williams, M. V., McNagny, S. E., Parker, R. M., & Baker, D. W. (1998). Ambulatory health care use by patients in a public hospital emergency department. *Journal of General Internal Medicine, 13*, 614-620. doi: 10.1046/j.1525-1497.1998.00184.x[76]

Rathlev, N., Almomen, R., Deutsch, A., Smithline, H., Li, H., & Visintainer, P. (2016). Randomized controlled trial of electronic care plan alerts and resource utilization by high frequency emergency department users with opioid use disorder. *Western Journal of Emergency Medicine, 17*, 28. doi: 10.5811/westjem.2015.11.28319[77]

Rea, H., Kenealy, T., Horwood, F., Sheridan, N., Parsons, M., Wemekamp, B., . . . Degeling, P. (2010). Integrated systems to improve care for very high intensity users of hospital emergency department and for long-term conditions in the community. *The New Zealand Medical Journal, 123*(1320), 76.[115]

Reinius, P., Johansson, M., Fjellner, A., Werr, J., Öhlén, G., & Edgren, G. (2013). A telephone-based case-management intervention reduces healthcare utilization for frequent emergency department visitors. *European Journal of Emergency Medicine, 20*, 327-334. doi:10.1097/MEJ.0b013e328358bf5a[78]

Riggs, J. E., Davis, S. M., Hobbs, G. R., Paulson, D. J., Chinnis, A. S., & Heilman, P. L. (2003). Association between early returns and frequent ED visits at a rural academic medical center. *American Journal of Emergency Medicine, 21*, 30-31. doi: 10.1053/ajem.2003.50017[79]

Robinson, K., Lucas, E., van den Dolder, P., & Halcomb, E. (2017). Living with chronic obstructive pulmonary disease: The stories of frequent attenders to the emergency department. *Journal of Clinical Nursing*, *27*, 48-56. doi: 10.1111/jocn.13842[80]

Ronksley, P. E., Liu, E. Y., McKay, J. A., Kobewka, D. M., Rothwell, D. M., Mulpuru, S., . . . Kline, J. A. (2016). Variations in resource intensity and cost among high users of the emergency department. *Academic Emergency Medicine, 23*, 722-730. doi:10.1111/acem.12939[81]

Ruger, J. P., Richter, C. J., Spitznagel, E. L., & Lewis, L. M. (2004). Analysis of costs, length of stay, and utilization of emergency department services by frequent users: implications for health policy. *Academic Emergency Medicine, 11*, 1311-1317. doi: 10.1197/j.aem.2004.07.008[82]

Saef, S. H., Carr, C. M., Bush, J. S., Bartman, M. T., Sendor, A. B., Zhao, W., ... & Melvin, C. L. (2016). A comprehensive view of frequent emergency department users based on data from a regional HIE. *Southern Medical Journal, 109*, 434. doi: 10.14423/SMJ.0000000000000488. [100]

Sandoval, E., Smith, S., Walter, J., Schuman, S. A. H., Olson, M. P., Striefler, R., ... & Hickner, J. (2010). A comparison of frequent and infrequent visitors to an urban emergency department. *The Journal of Emergency Medicine, 38*, 115-121. doi: 10.1016/j.jemermed.2007.09.042[83]

Schneider, K. C., & Dove, H. G. (1983). High users of VA emergency room facilities: Are outpatients abusing the system or is the system abusing them?. *Inquiry*, *20,* 57-64.[45]

Skinner, J., Carter, L., & Haxton, C. (2009). Case management of patients who frequently present to a Scottish emergency department. *Emergency Medicine Journal, 26*, 103-105. doi:10.1136/emj.2008.063081[84]

Skyttner, L. (2001). *General systems theory: Ideas & applications*. River Edge, N.J: World Scientific.

Solberg, R. G., Edwards, B. L., Chidester, J. P., Perina, D. G., Brady, W. J., & Williams, M. D. (2016). The prehospital and hospital costs of emergency care for frequent ED patients. *The American Journal of Emergency Medicine, 34*, 459-463. doi: 10.1016/j.ajem.2015.11.066[85]

Soril, L. J. J., Leggett, L. E., Lorenzetti, D. L., Noseworthy, T. W., & Clement, F. M. (2016). Characteristics of frequent users of the emergency department in the general adult population: A systematic review of international healthcare systems. *Health Policy, 120,* 452-461. doi:10.1016/j.healthpol.2016.02.006

Stergiopoulos, V., Gozdzik, A., de Bibiana, J. T., Guimond, T., Hwang, S. W., Wasylenki, D. A., & Leszcz, M. (2016). Brief case management versus usual care for frequent users of emergency departments: the Coordinated Access to Care from Hospital Emergency Departments (CATCH-ED) randomized controlled trial. *BMC Health Services Research, 16*, 432. doi: 10.1186/s12913-016-1666-1[86]

Stokes-Buzzelli, S., Peltzer-Jones, J. M., Martin, G. B., Ford, M. M., & Weise, A. (2010). Use of health information technology to manage frequently presenting emergency department patients. *Western Journal of Emergency Medicine*, *11*(4), 348.

Sun, B. C., Burstin, H. R., & Brennan, T. A. (2003). Predictors and outcomes of frequent emergency department users. *Academic Emergency Medicine, 10*(4), 320-328.[11]

Thakarar, K., Morgan, J. R., Gaeta, J. M., Hohl, C., & Drainoni, M. L. (2015). Predictors of frequent emergency room visits among a homeless population. *PLoS One, 10*, e0124552. doi: 10.1371/journal.pone.0124552[87]

Ullman, R., Block, J. A., & Stratmann, W. C. (1975). An emergency room's patients: their characteristics and utilization of hospital services. *Medical Care, 13*(12), 1011-1020.[88]

U.S. Census Bureau (2016). *Population estimates*. Retrieved from https://www.census.gov/quickfacts/fact/table/US/PST045216

Ustulin, M., Woo, J., Woo, J. T., & Rhee, S. Y. (2017). Characteristics of Frequent Emergency Department Users with Type 2 Diabetes Mellitus in Korea. *Journal of Diabetes Investigation.* Advance online publication. doi: 10.1111/jdi.12712[89]

Vandyk, A. D., VanDenKerkhof, E. G., Graham, I. D., & Harrison, M. B. (2014). Profiling frequent presenters to the emergency department for mental health complaints: Socio-demographic, clinical, and service use characteristics. *Archives of Psychiatric Nursing, 28*, 420-425. doi: 10.1016/j.apnu.2014.09.00[123]

van Tiel, S., Rood, P. P. M., Bertoli-Avella, A. M., Erasmus, V., Haagsma, J., van Beeck, E., . . . Polinder, S. (2015). Systematic review of frequent users of emergency departments in non-US hospitals: State of the art. *European Journal of Emergency Medicine, 22*, 306-315. doi:10.1097/MEJ.0000000000000242[90]

vonBertalanffy, L. (1950). *An outline of general system theory*. Retrieved on January 1, 2018 from http://www.isnature.org/Events/2009/Summer/r/Bertalanffy1950-GST_Outline_SELECT.pdf

vonBertalanffy, L. (2008). An outline of general system theory. Emergence: Complexity and Organization. *Emergent Publications, 10*, 103. doi: 10.emerg/10.17357.68d4f3e4bc6cef486e74d7d28e6ceca4

Vu, F., Daeppen, J. B., Hugli, O., Iglesias, K., Stucki, S., Paroz, S., ... & Bodenmann, P. (2015). Screening of mental health and substance users in frequent users of a general Swiss emergency department. *BMC Emergency Medicine, 15*, 27. doi: 10.1186/s12873-015-0053-2[91]

Wajnberg, A., Hwang, U., Torres, L., & Yang, S. (2012). Characteristics of frequent geriatric users of an urban emergency department. *The Journal of Emergency Medicine, 43*, 376-381. doi: 10.1016/j.jemermed.2011.06.056[92]

Walonick, D. (1993). *General systems theory*. Retrieved from http://www.statpac.org/walonick/systems-theory.

Watase, H., Hagiwara, Y., Chiba, T., Camargo, J., Carlos A, Hasegawa, K. (2015). Multicentre observational study of adults with asthma exacerbations: Who are the frequent users of the emergency department in japan? *British Medical Journal Open, 5*, e007435-e007435. doi:10.1136/bmjopen-2014-007435[37]

Weber, E. J. (2012). Defining frequent use: The numbers no longer count. *Annals of Emergency Medicine, 60,* 33-34. doi: 10.1016/j.annemergmed.2012.02.019[93]

Williams, E. R. L., Guthrie, E., Mackway-Jones, K., James, M., Tomenson, B., Eastham, J., & McNally, D. (2001). Psychiatric status, somatisation, and health care utilization of frequent attenders at the emergency department: A comparison with routine attenders. *Journal of Psychosomatic Research, 50*, 161-167. doi:10.1016/S0022-3999(00)00228-2[94]

Wise-Harris, D., Pauly, D., Kahan, D., de Bibiana, J. T., Hwang, S. W., & Stergiopoulos, V. (2017). "Hospital was the only option": Experiences of frequent emergency department users in mental health. *Administration and Policy in Mental Health and Mental Health Services Research, 44*, 405-412. doi: 10.1007/s10488-016-0728-3[95]

Wong, J., Marr, P., Kwan, D., Meiyappan, S., & Adcock, L. (2014). Identification of inappropriate medication use in elderly patients with frequent emergency department

visits. *Canadian Pharmacists Journal/Revue des Pharmaciens du Canada, 147*, 248-256. doi: 10.1177/1715163514536522[96]

Woo, J. H., Grinspan, Z., Shapiro, J., & Rhee, S. Y. (2016). Frequent users of hospital emergency departments in Korea characterized by claims data from the national health insurance: A cross sectional study. *PLoS One, 11*, e0147450. doi:10.1371/journal.pone.0147450[97]

Wooden, M. D., Air, T. M., Schrader, G. D., Wieland, B., & Goldney, R. D. (2009). Frequent attenders with mental disorders at a general hospital emergency department. *Emergency Medicine Australasia, 21*, 191-195. doi: 10.1111/j.1742-6723.2009.01181.x.[118]

Wu, J., Grannis, S. J., Xu, H., & Finnell, J. T. (2016). A practical method for predicting frequent use of emergency department care using routinely available electronic registration data. *BMC Emergency Medicine, 16*, 12. doi:10.1186/s12873-016-0076-3

Zarisfi, F., Hong, Q. E., Seah, P. S. J., Li, H., Yap, S., & Ong, M. E. H. (2014). Retrospective study of elderly frequent attenders presenting with chest pain at emergency department. *International Journal of Emergency Medicine, 7*, 35. doi: 10.1186/s12245-014-0035-2[121]

Zuckerman, S., & Shen, Y. C. (2004). Characteristics of occasional and frequent emergency department users: Do insurance coverage and access to care matter? *Medical Care, 42*, 176-182. doi: 10.1097/01.mlr.0000108747.51198.41[98]

Figure 1. Flowchart of the Systematic Review

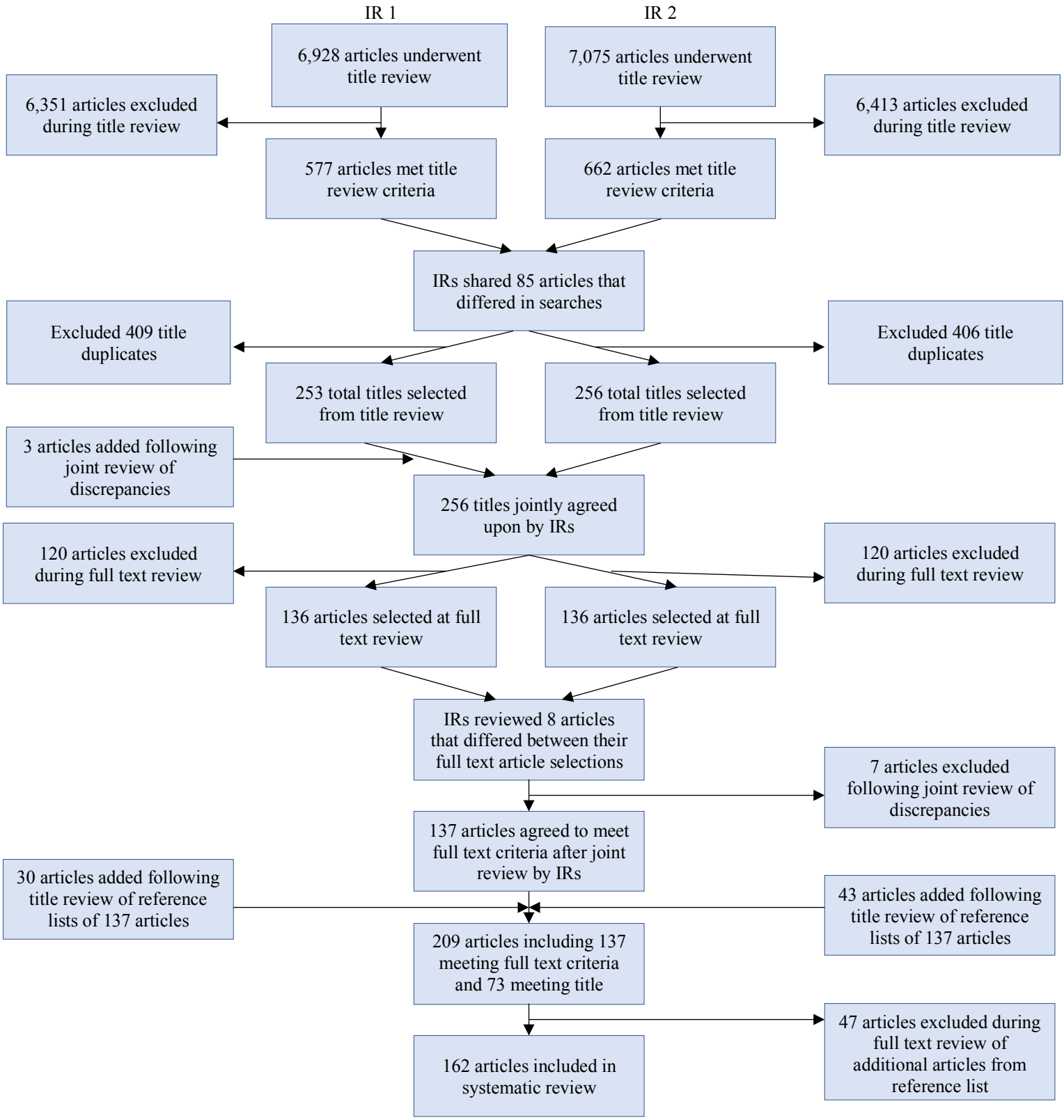


Table 1. Most Commonly Used Definitions and Justifications for Each Subgroup of Frequent ED Use

Diagnostic Category	Definition	Justification
General Articles that included all patients, all diagnoses	1. ≥ 4 visits in 1 year (n=26)[7-8, 11, 13-14, 19, 32, 33, 35, 38-39, 41, 49, 53, 54, 59, 67, 91, 97, 100-106]	1. None given (n=12)
		2. Common definition (n=9)[6-8, 12, 19, 24, 28, 31-33, 41, 48, 53-54, 56, 63, 71, 104, 107]
		3. Cited literature without explanation(n=2)*[4, 29, 54, 56]
		3. Based on study data (n=2)*
	2. ≥ 5 visits in 1 year (n=15)[9, 28-29, 57, 70-71, 85, 110-117]	1. None given (n=4)
		2. Common definition (n=3)[28, 53, 119]
		3. Cited literature without explanation (n=2)*[24, 48, 117-118]
		3. Validated definition (n=2)*[53]
	3. ≥ 3 visits in 1 year (n=8)[3, 40, 52, 67, 81, 83, 98, 108]	1. Cited literature without explanation (n=2)*[48, 82, 88, 98]
		1. None given (n=2)*
		1. Unique definition not based on data or literature (n=2)*
Targeted Populations Articles targeting homeless, geriatric, low income and uninsured, Medicaid, Medicare, prisoner, ambulance transported non-emergency, and veteran populations	1. ≥ 4 visits in 1 year (n=8)[23, 51, 60, 64, 96, 119-121]	1. None given (n=4)
		2. Common definition (n=3)[4, 35, 41, 48, 53, 68]
	2. ≥ 2 visits in 1 year (n=3)[47, 87,124]	1. None given (n=2)
Targeted Diagnoses Articles targeting heart failure, asthma, chronic diseases, community-onset monomicrobial enterobacteriaceae bacteremia, COPD, mental health and substance abuse, migraines, adverse childhood experiences and health locus of control, sickle cell disease, systemic lupus type 2 diabetes, and unresolved pain	1. ≥ 3 visits in 1 year (n=8)*[2, 26, 37, 50, 65, 69, 72, 80]	1. Cited literature without explanation (n=3)[12, 22, 34, 41]
		2. None given (n=2)
	1. ≥ 5 visits in 1 year (n=8)*[1, 43-44, 73-74, 86, 95, 123]	1. None given (n=6)
	2. ≥ 4 visits in 1 year (n=6)[15-16, 18, 42, 77, 89]	1. None given (n=3)
		2. Common definition (n=2)[41, 48, 71]

*Definitions or justifications for definition used same number of times
None given = no justification or citations
Definition superscripts denote articles that used each given definition
Justification superscripts denote articles that were cited as part of the justification given by articles using the definition to which it corresponds

Table 2. Demographics

	Studies of Frequent Users Only	**Studies Comparing Frequent and Non-frequent Users**	
		Frequent Users	Non-frequent Users
Age (years)	51.2	44.8	38.2
Studies reporting Sample size	41 of 83 N=289,773	38 of 80 N=3,853,682	
Gender			
Men	34,878 (48%)	1,431,979 (3%)	22,389,440 (42%)
Women	35,933 (52%)	2,605,989 (5%)	26,816,573 (50%)
Studies reporting Sample size	32 of 83 N=70,811	45 of 80 N=53,241,072	
Race			
Asian	44 (1%)	2,525 (0%)	33,996 (1%)
Black	1,716 (30%)	91,087 (3%)	355,894 (12%)
Latino	1,421 (25%)	38,557 (6%)	172,652 (6%)
Multiracial	n/a	7 (0%)	41 (0%)
Native	4 (0%)	2,581 (0%)	9,744 (0%)
American	279 (5%)	14,412 (0%)	69,650 (2%)
Other/Unknown	2,182 (39%)	25,1627 (9%)	1,855,437 (64%)
White	16 of 83		
Studies reporting Sample size	N=5,646	14 of 80 N=2,897,109	

Age results are weighted means based on articles reporting this variable and sample size
Studies were not included if they did not report sample size and/or data for all subgroups of a variable, and when the sum of all subgroups did not equal the total sample size reported

CHAPTER 4: METHODOLOGY

Nearly nineteen percent (18.8%) of U.S. adults age eighteen years or older visit the emergency department (ED) in a given year (Centers for Disease Control, 2016). A small portion of these account for many visits (so-called "frequent users"; Doupe et al., 2012). While there is undoubtedly a group that experiences a higher frequency of ED use, both the way "frequent ED use" has been defined and the "problem" (as it has been framed in terms of ED use), has ubiquitously focused on number of visits, in a linear, unidimensional fashion. This has resulted in research, practice, and policy that examines both the phenomenon and patients through the lens of whether they have visited "too many" times or measured outcomes based on the goal of reducing the number of visits rather than examining whether use was appropriate, patients received appropriate kinds of care, or their service needs were met, for example.

We have, however, gained an important perspective from the linear approach to ED use (i.e., the focus on the number of ED visits alone). For example, we understand that there is a population of individuals that visit the ED at a higher rate than the general population, and these individuals have greater healthcare needs (Byrne et al., 2003; Fuda & Immekus, 2006; Hunt, Weber, Showstack, Colby, & Callahan, 2006), and greater overall healthcare usage across healthcare services (e.g. primary care, specialty care, etc.; Byrne et al., 2003; Chan & Ovens, 2002; Hansagi, Olsson, Sjöberg, Tomson, & Göransson, 2001). However, this linear focus eschews the fact that ED use, including frequent use, exists along a continuum, and a unilevel descriptive definition of this issue is an oversimplification at best (Weber, 2012). A linear perspective on ED use has highlighted the need for a new, systemic approach to understanding ED utilization. Such an approach, based in systems theory (vonBertalanffy, 1968), would allow us to expand beyond a unilevel understanding of use, to incorporate as many levels as possible-

through a systemic lens, including factors such as patient demographics, geographic information, diagnoses, interventions, etc. This new approach would not happen within the frame of a number of visits, but rather, this approach would allow multiple systemic levels to be considered together in order to see which patient characteristics coalesce to form unique patient cohorts.

To date, there are no studies that explore the systemic underpinnings of ED use. A number of articles have attempted to use data analysis to define frequent users by constructing empirical means for which to categorize ED users. These studies were based on patient characteristics, rather than allowing a particular number of visits to either guide their analysis or define frequent ED use outright (Doupe et al., 2012; Locker, Baston, Mason, & Nicholl, 2007; Wu, Grannis, Xu, & Finnell, 2016). One such study compared differences in observed and theoretical frequency distribution in order to develop a definition of frequent ED use, and concluded that there is a group of patients that present to the ED repeatedly due to non-random events, and that the concept of "frequent user" is legitimate (Locker, Baston, Mason, & Nicholl, 2007). However, they also found that there is no clear cut-off between chance and frequent users when using an expected frequency distribution, as the two distributions theoretically continue to infinity. Thus, they asserted that any visit cut-off to define frequent use is arbitrary. Another empirically-driven study used logistical regression models with select patient characteristics viewed by ED visit frequency to establish "breakpoints" in use trends (Doupe et al., 2012). Ultimately this study also chose a cut-off point based on number of visits to define frequent ED use, even though patient characteristics were found to exist along the continuum of use and overlap across this breakpoint. Pereira and colleagues (2016) presented empirical work at a conference using machine learning models to predict frequent ED use based on patient characteristics, however they used number of visits to define frequent use, and the incorporation

of patient characteristics was intended to improve the predictive accuracy of their model based on number of visits. Wu, Grannis, Xu, and Finnell (2016) developed logistic regression models based on patient characteristics and use to predict ED visits across multiple years. However, in this study they used visit cut-points ranging from eight to 16 visits over a two-year period to fit their models, meaning that they still chose a visit range to identify frequent users. In order to expand beyond a unilevel understanding of use, this study proposes to incorporate as many systemic levels associated with emergency department use as possible, including factors such as patient demographics, geographic information, diagnoses, interventions, etc.

Thus, in an effort to aim for a more holistic understanding of factors associated with ED use, and to define ED patient subgroups, the purpose of this study is to gain an understanding of systemic factors that contribute to ED use.

Hypotheses

The purpose of this study was to (a) determine if clustering algorithms could be used to identify unique ED patient clusters or cohorts and (b) test the following specific hypotheses:

1. Clustering with feature selection (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015) produces better fitting clusters than clustering based on number of visits to the ED. See data analysis section for a definition of best fit. Feature selection is the process in data mining used to identify the most relevant features for classification in clusters. Relevant features of a dataset are detected, and irrelevant and redundant ones are discarded with the goal of obtaining a subset of items that properly describe the issue or problem of focus while minimizing negative effects on performance of model (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015).

2. Using feature selection to identify patient characteristics to cluster produces better fitting clusters than using select patient characteristics based on the frequent ED user literature and number of visits.

3. Using features selection, patients that visit the ED across multiple, consecutive years will be clustered into different cohorts than those that only visit the ED during a single year, with no use in the following year.

Study Design

The primary aim of this study was to explore systemic factors associated with ED use. To address the hypotheses outlined above, feature selection and machine learning clustering models were employed to develop patient cohorts with multiple, comprehensive, state-level databases.

Databases

The State Emergency Department Databases (SEDD) and State Inpatient Databases (SID), which are a part of the Healthcare Cost and Utilization (HCUP) set of databases (Healthcare Cost and Utilization Project, 2018c), were used to create patient clusters or cohorts in this study. These databases are developed through a Federal-State-Industry partnership bringing together data collection from State data organizations, hospital associations, private data organizations, and the Federal government, and sponsored by the Agency for Healthcare Research and Quality (AHRQ). HCUP includes the largest collection of longitudinal hospital care data in the United States, that includes all-payer, encounter-level information.

SEDD are longitudinal, State-specific databases of emergency department visits that occur in each state. Currently thirty-six states participate in the SEDD (Healthcare Cost and Utilization Project, 2018d). These datasets capture emergency visits at hospital-affiliated EDs that do not result in hospitalization. ED visits that result in inpatient stays are captured in the

SID, thus necessitating the use of this database as well (as discussed below). The SEDD files include all patients, regardless of payer, providing a unique view of ED care in a State over time.

The SEDD contain a core set of clinical and nonclinical information on all patients, including individuals covered by Medicare, Medicaid, or private insurance, as well as those who are uninsured (Health Care Cost and Utilization Project, 2018d). These datasets contain clinical and resource-use information that is included in a typical discharge abstract, with safeguards to protect the privacy of individual patients, physicians, and hospitals. The SEDD contain more than 100 clinical and non-clinical variables included in a hospital discharge abstract, such as (a) all-listed diagnoses and procedures; (b) patient demographics characteristics (e.g., sex, age, and, for some States, race); (c) expected payment source; (d) total charges; (e) hospital identifiers that permit linkage to hospital inpatient databases, such as the SID. Elements included in the SEDD are not always available for all States. The SEDD are calendar year files based on discharge date.

Information about patients initially seen in the ED and then admitted to the hospital are included in the SID (Healthcare Cost and Utilization Project, 2018e). While the extraction of ED visits from this data set expands the number of visits for analysis, the true benefit is in its semantics – ED visits leading to admittance. Knowing, for instance, that a series of SEDD visits resulted in an SID ED to inpatient scenario might impact results. Thus, SID is an important inclusion in our analysis.

SID are State-specific files that contain all inpatient care records in participating states. The SID files include all patients, regardless of payer, providing a unique view of inpatient care in a State over time. SID contain a core set of clinical and nonclinical information on all patients, including individuals covered by Medicare, Medicaid, or private insurance, as well as those who are uninsured. The SID contain clinical and resource-use information that is included in a typical

discharge abstract, with safeguards to protect the privacy of individual patients, physicians, and hospitals. The SID contain more than 100 clinical and nonclinical variables included in a hospital discharge abstract, such as (a) principal and secondary diagnoses and procedures; (b) admission and discharge status; (c) patient demographics characteristics (e.g., sex, age, and, for some States, race); (d) expected payment source; (e) total charges; (f) length of stay. Variables included in the SID are not always available for all States. The SID are calendar year files based on discharge date.

Data elements available in the SEDD and SID are coded by HCUP to make them anonymous, and to make analysis more feasible (Health Care Utilization Project, 2018b). Data elements such as diagnosis and procedure codes are retained in the original form provided by the data source. Physician and personal identifiers are encrypted into synthetic values. Demographics such as sex and race, as well as expected primary pay source are recoded into uniform coding schemes. Data elements such as age, length of stay, and day of principal procedure are calculated when possible. Finally, elements such as diagnosis related groups (DRGs) and clinical classifications software (CCS) are assigned using external algorithms.

Data elements in the SEDD and SID are defined as numeric or character (e.g. weight, prescription name; health Care Utilization Project, 2018b). Missing data and invalid data are denoted by HCUP data creators with specific characters in order to be easily identified. Validity checks are also run by HCUP on diagnosis- and procedure-related data elements. Codes to denote missing, valid, invalid, or inconsistent diagnosis and procedure codes are included in order to easily identify missing, invalid, and inconsistent codes.

Sample

Florida SEDD and SID were selected for this study based on an evaluation of which states had the most complete data for the years 2009 to 2015 (the most recent year available) and included the "revisit variable" (which allows tracking of a patients within a given year). Florida was found to have the most visits available per year from 2009 to 2015 (6.53-8.49 million) and contain the revisit variable for all seven years of data. Additionally, it was discovered through codebook review that patient tracking extends across years, as Florida has maintained a uniform identifier generation scheme for all years analyzed (A. Henderson, personal communication, November 8, 2017; Healthcare Cost and Utilization Project, 2017). Minors were not included in our study as this data was not manually validated (Healthcare Cost and Utilization Project, 2017). X% of patients were minors and therefore excluded. This reduced the number of patients in our study from X million to X million.

SEDD and SID for the state of Florida can be purchased through the HCUP central distributor. Costs vary by State and data year. All HCUP data users, including data purchasers and collaborators, are required to complete the online HCUP Data Use Agreement Training Tool, and read and sign the Data Use Agreement for State Databases. SED and SID datasets came in ASCII format, and were delivered to the researcher by secure digital download.

Procedures

Following IRB approval, and HCUP data use training and agreement signing, the SEDD and SID datasets from 2009-2015 were obtained by purchase from the HCUP central distributor. SED and SID datasets came in ASCII format, and were delivered to the researcher by secure digital download.

Due to the fact that the United States transitioned from using ICD-9-CM to ICD-10-CM/PCS code sets for reporting medical diagnoses and inpatient procedures in October 2010, a portion of the codes from that year needed to be converted to ICD-9-CM for analysis and comparison (Health Care Cost and Utilization Project, 2018a). ICD-10-CM/PCS consists of two parts (a) ICD-10-CM: diagnosis coding on inpatient and outpatient data; (b) ICD-10-PCS: procedure coding on inpatient data. HCUP State databases are annual, calendar-year files, and as such the introduction of ICD-10 on October 1, 2015 means that the 2015 databases include a combination of codes, including nine months of data with ICD-9-CM codes (Jan 1, 2015 to September 30, 2015), and three months of data with ICD-10-CM/PCS codes (October 1, 2015 to December 31, 2015). As a result, the State databases have two separate files for 2015 (a) one for the first nine months of the year, in which ICD-9-CM codes were used; (b) a second in which the last three months of the year, in which ICD-10-CM/PCS codes were used. If a patient visit record had a discharge date between January 1, 2015, and September 30, 2015, it was retained in the quarter 1 to quarter 3 file and includes ICD-9-CM data. If the record has a discharge date between October 1, 2015, and December 31, 2015, it was retained in the quarter 4 file and includes ICD-10-CM/PCS data. For the purpose of this study, The Centers for Medicare & Medicaid Services (CMS) reverse General Equivalence Mappings (GEMs) were used to convert ICD-10-CM/PCS to ICD-9-CM.

To convert the ICD-10-CM/PCS codes to ICD-9-CM, a custom, bulk, reverse GEM mapping application was written in Java. This application takes as input the SEDD/SID data beginning October 1, 2015, extracts the ICD-10-CM/PCS codes, maps them to their ICD-9-CM general equivalences, and produces a document identical to the input save the mapped codes.

Data Analysis

For this study, feature selection (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015) and cluster analyses were used to create patient cohorts (Han & Kamber, 2006) based on systemic data. Feature selection detects relevant features of a dataset with the goal of obtaining a subset of features that properly describes the issue or problem of focus while minimizing negative effects on performance of model (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015). Cluster analysis is the task of grouping a set of objects in such a way that objects in the same group are more similar to each other than to those in other groups (Han & Kamber, 2006).

Cluster analyses with feature selection were compared to cluster analyses utilizing operationalized definitions of frequent ED use to group patients (e.g. Doupe et al., 2012; Locker, Baston, Mason, & Nicholl, 2007). Cluster analysis using feature selection was chosen as a comparison to clustering based on number of ED visits so as to compare the fit of unilevel to multi-systemic clustering of ED patients. For the purposes of comparison, we chose the most common definition cited in the literature to define frequent use for our comparison (e.g. four or more visits in 12 months; Goodman et al., 2018). Although the most common definition used in the literature on frequent ED use, this definition of four or more visits in 12 months, is not empirically- or theoretically-based. Thus, a systemic-based cluster (using cluster analyses with feature selection) and linear-based clusters (using four or more visits in 12 months) will be compared for best fit. The following is a richer description of the feature selection process.

Feature selection. Feature selection is a process by which relevant features of a dataset are detected and irrelevant and/or redundant ones are discarded with the goal of obtaining a subset of features that properly describes the issue or problem of focus while minimizing

negative effects on performance of model (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015). Advantages to feature selection include, (a) improving the performance of machine learning algorithms, (b) gaining knowledge about the process being studying, and (c) data reduction that thereby limits the storage requirements and thus costs (Guyon, Gunn, Nikravesh, & Zadeh, 2006).

There are many approaches to features selection (Han & Kamber, 2006); each having their own benefits and drawbacks. The clusters we proposed to generate were constructed using the data for the selected features. The efficacy of our analysis depended on the information captured in those feature-restricted datasets. That is, if the features were poorly selected, the derived clusters would be inadequate for identifying meaningful patient subsets, resulting in model degradation. The challenge was determining which feature selection algorithm was the "best" for the given dataset and subsequent analysis; which is entirely dependent on the study. Herein, five feature selection algorithms were employed to produce feature-restricted datasets for subsequent clustering and comparative analysis. These approaches to feature selection included (a) forward selection (RapidMiner, n.d.-a), (b) backward elimination (RapidMiner, n.d.-b), (c) optimize selection (RapidMiner, n.d.-c) – forward selection, (d) optimize selection – backward elimination, and (e) optimize selection – evolutionary (RapidMiner, n.d.-d).

Forward selection began with an empty set of selected features and added (i.e., selected) one feature per round (RapidMiner, n.d.-a). The selected feature was the one resulting in the greatest performance gain (i.e., benefit) from the remaining set of unselected features. This operation continued until the benefit of adding the next feature was negligible or zero (i.e., it converged; RapidMiner, n.d.-d). Backward elimination began with all features and removed (i.e., eliminated), at each round, the one decreasing overall performance the least. This continued until

some minimum threshold was reached (i.e., it converged). The threshold was either a minimum overall performance level or maximum allowed decrease in performance per feature (RapidMiner, n.d.-b). Optimize selection – forward selection/backward elimination are RapidMiner variations of the aforementioned algorithms. Instead of selecting a single feature at each round, *k* were chosen. This provided alternatives in case a solution became trapped in some local optima (i.e., the algorithm finds a relatively "good" solution, but not the best as it gets trapped in the "valley" of the local optima, without the ability to "climb out" in search of the deepest one (the global optimum)); thus, failing to construct a viable feature set. That is, after a few rounds, the algorithm converges, yet the resulting feature set is too small to adequately describe the problem. Hence, the process continued until all *k* solutions converged with the best solution (RapidMiner, n.d.-c). Forward selection and backward elimination (and their optimized selection variants) are "greedy" algorithms (RapidMiner, n.d.-c). At each selection/elimination point, they followed a very simple rule (i.e., heuristic) – choosing the move (or top *k* moves) that provided the most benefit at that moment (i.e., the locally optimal move). This sacrificed performance for speed, as it is very fast, but generally resulted in poor solutions for large feature spaces (e.g. datasets with many variables; Corman, Leiserson, Rivest, & Stein 2009). The last algorithm, optimize selection – evolutionary, sought to find the set of features that maximized overall performance within a reasonable amount of time (RapidMiner, n.d.-c). There is an optimize selection – brute force option which evaluates all feature combinations, but for even a moderate number of features, the exponential runtime becomes infeasible. For instance, ten features require $2^{10} = 1{,}024$ combination evaluations, twenty necessitates $2^{20} = 1{,}048{,}576$, and so on. With hundreds or thousands of features (as there are herein), the execution time of brute force would be measured in millennia; hence, the evolutionary approach was warranted.

Evolutionary algorithms are a class of heuristic algorithms designed to mimic natural processes (RapidMiner, n.d.-d). The activity imitated in the optimize selection – evolutionary algorithm was based on the properties of genetic inheritance, mutation, selection, and crossover, as defined in the field of genetic algorithms (GA). GA's, designed by Holland (1975), began with a random population of size *p* (i.e., sets of random features) from which pairs (called parents) were crossed to produce offspring. Crossing is simply the process of selecting a certain number of features from each parent to produce an offspring. During crossover, mutations can arise which alter the state of a feature with some probability. The goal was to construct a high quality, diverse population of solutions. This continued until convergence (generally defined by a minimum threshold of performance improvement), at which point, the best solution was selected. GA's advantage over forward selection and backward elimination was its ability to evaluate a greater number of solutions without becoming trapped in local optima as easily. It does, however require more time, but typically locates better solutions, especially in high-dimensional spaces (Burke & Kendall, 2005; Goldberg, 1989; Holland, 1975; Mitchell, 1998).

Clustering. Following the completion of feature selection (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015), a number of clustering techniques (discussed later in this section) were applied to selected attributes from the dataset. Cluster analysis is a process by which physical or abstract objects are grouped into classes of similar objects (Han & Kamber, 2006). A cluster is a collection of data objects that are similar to one another and dissimilar to the objects in other clusters. Because a cluster of data can be treated as a collective group, clustering is considered a form of data compression. In this process, data are first partitioned into groups based on data similarity, and then labels are assigned to the relatively few groups (clusters).

Advantages of clustering include its adaptability to changes in data over time, and its usefulness in identifying features that distinguish different groups from one another.

Clustering is a form of unsupervised learning, meaning that it does not rely on manually predefined classes or class-labeled training examples (Han & Kamber, 2006). As such, clustering models learn by observation, rather than learning by example. There are a number of requirements in order for successful clustering. These include (a) scalability; (b) ability to deal with different types of attributes; (c) discovery of clusters with arbitrary shape; (d) minimal requirements for knowledge to determine input parameters; (e) ability to deal with noisy data; (f) insensitivity to the order of input records; (g) high dimensionality; (h) constraint-based clustering; (i) interpretability and usability.

Scalability addresses whether the clustering model can be applied to large datasets without producing biased results (Han & Kamber, 2006). Many algorithms are designed to cluster numerical data, however studies such as this require clustering of other types of data, such as nominal, ordinal, binary, or a mixture of data types; thus, it is important that the models can deal with different data attributes. Many clustering algorithms determine clusters based on Euclidean or Manhattan distance measures and tend to find spherical clusters with similar size and density, however it is important that algorithms that can detect clusters of arbitrary shape be used. Likewise, many clustering algorithms require input of specific parameters into the model (e.g. number of desired clusters), however clusters can be sensitive to this input data, and parameters can be difficult to determine for highly dimensional data. Given that healthcare data has vast numbers of variables (e.g. blood pressure, weight, cholesterol level), and many variables in healthcare data are inter-related (e.g. weight and blood pressure), it is important that there be minimal requirements for knowledge to determine input parameters. Most datasets contain

outliers, missing, unknown, or inaccurate data, and thus it is important that clustering algorithms have the ability to deal with noisy data, otherwise clusters of poor quality could be developed. It is important to develop incremental clustering algorithms and algorithms that are insensitive to the order of data input, otherwise algorithms could develop considerably different clusters from clusters produced by the same clustering algorithm with a different attribute order depending on the order of variable input (i.e. an algorithm with attributes presented in the order 1, 2, 3, 4 would produce a different set of clusters than one with a different order, such as 2, 4, 3, 1). Clustering may need to be performed under specific constraints (such as when sub-clustering patients by income or race), and thus it is preferred that good clustering behavior occur while still satisfying such constraints. Finally, it is important that clustering results be interpretable, logical, and usable, so that the findings can be applied.

In order to determine which algorithm would have the best performance on each of our hypotheses, seven unique clustering algorithms were applied for each hypothesis. These clustering algorithms included (a) *k*-means, (b) *k*-medoids, (c) density-based spatial clustering of applications with noise (DBSCAN), (d) expectation maximization (EM), (e) support vector, (f) agglomerative, and (g) top down (RapidMiner, n.d.-e). *k*-means is the most commonly used clustering algorithm and is relatively scalable and efficient in processing large data sets due to the computational complexity of the algorithm (Han & Kamber, 2006). *k*-medoids are a variation of *k*-means with a slight difference in the centroids, which may affect clustering. DBSCAN is able to discover clusters of arbitrary shape in spatial databases with noise. EM, which is an extension of the *k*-means paradigm, is a popular algorithm that does not impose strict boundaries between clusters. Support vectors tend to be less prone to overfitting than some other methods. Agglomerative are easy to implement and output a hierarchy of clusters (i.e. clusters that have a

predetermined ordering from top to bottom) that can be more informative than flat clusters (i.e. clusters that are coherent internally, but different from each other in non-hierarchical ways). Top down may be more efficient and produce more accurate hierarchies than bottom up clustering algorithms.

For *k*-means, the number of clusters that the algorithm would return was determined by the researcher (Han & Kamber, 2006). *k*-means started assigning a number of points, corresponding to the number of clusters that were set at the beginning, as *centroids* to the potential clusters. All points were assigned to the nearest centroid as defined by a measurement (e.g. Euclidean distance). Then, the centroids were recalculated by averaging all the points in a given cluster. This step was repeated until the centroid no longer moved. *k*-medoids clustering, a variation on *k*-means, calculated centroids that were actual points in the cluster, as opposed to an imaginary one (e.g., the average) in *k*-means. DBSCAN clustered starting with an arbitrary starting point that had not been analyzed yet. This point's epsilon-neighborhood (given distance from this point to other points) was retrieved, and in each space where a sufficient number of points existed, a cluster was started; otherwise, the point was labeled as noise. Points labeled as noise could later be found in a sufficiently sized epsilon-environment of a different point and then were made a part of that cluster. EM clustering is similar to *k*-means clustering, with two differences (a) the goal of EM clustering is to estimate the means and standard deviations for each cluster in order to maximize the likelihood of the observed distribution (EM clustering attempts to approximate the observed distributions of values based on mixtures of different distributions in different clusters); (b) support vector clustering maps data points from a data space to a high dimensional feature space using a Gaussian kernel (i.e. a popular kernel function (a class of algorithms for pattern analysis)). In the space in which clustering occurred, the

smallest sphere that enclosed the data was searched. This sphere was mapped back to the space the data was in, where it formed a set of contours which enclosed the data points. These contours were interpreted as cluster boundaries. Points enclosed by each separate contour were associated with the same cluster. Agglomerative clustering used a bottom-up approach whereby each observation started in its own cluster, and pairs of clusters merged as one moved up the hierarchy until all the points were in a single cluster or until specific termination conditions were satisfied. In top down clustering, all the data began in one cluster, which then split into more specialized/differentiated clusters. In essence, it identified and extricated sub-groupings from a cluster based on extant features and data relatedness.

Summary

The methodology for this study was grounded in systems theory (vonBertalanffy, 1968). Our methodology was constructed to determine if clusters using systemic information about ED patient use were more accurate and better fitting than those based on linear data. For the purposes of comparison, we chose the most common definition cited in the literature to define frequent use for our comparison (e.g. four or more visits in 12 months; Goodman et al., 2018). Although the most common definition used in the literature on frequent ED use, it is not empirically- or theoretically-based. For this study, feature selection (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015) and cluster analyses were used to create patient cohorts (Han & Kamber, 2006) based on systemic data. The former approach was compared to clusters operationalizing frequent use by the number of visits to the ED over a given period of time and select patient characteristics (e.g. Doupe et al., 2012; Locker, Baston, Mason, & Nicholl, 2007).

REFERENCES

Bolón-Canedo, V., Sánchez-Maroño, N., & Alonso-Betanzos, A. (2015). *Feature selection for high-dimensional data*. Cham, Switzerland: Springer.

Burke, E., Kendall, G. (2005). *Search methodologies introductory tutorials in optimization and decision support techniques*. Springer: New York.

Byrne, M., Murphy, A. W., Plunkett, P. K., McGee, H. M., Murray, A., & Bury, G. (2003). Frequent attenders to an emergency department: A study of primary health care use, medical profile, and psychosocial characteristics. *Annals of Emergency Medicine, 41*, 309-318. doi:10.1067/mem.2003.68

Centers for Disease Control (2016). *Health, United States, 2016: With chartbook on long-term trends in health*. Retrieved from: https://www.cdc.gov/nchs/data/hus/hus16.pdf#076

Chan, B. T., & Ovens, H. J. (2002). Frequent users of emergency departments. Do they also use family physicians' services?. *Canadian Family Physician, 48*(10), 1654-1660.

Corman, T.H., Leiserson, C.E., Rivest, R.L. & Stein, C. (2009). Introduction to algorithms (3rd ed). MIT Press: Cambridge, Massachusetts.

Doupe, M. B., Palatnick, W., Day, S., Chateau, D., Soodeen, R. A., Burchill, C., & Derksen, S. (2012). Frequent users of emergency departments: developing standard definitions and defining prominent risk factors. *Annals of Emergency Medicine, 60*, 24-32. doi: 10.1016/j.annemergmed.2011.11.036

Fuda, K. K., & Immekus, R. (2006). Frequent users of Massachusetts emergency departments: A statewide analysis. *Annals of Emergency Medicine, 48*, 16-e1. doi: 10.1016/j.annemergmed.2006.03.001

Goldberg, D.E. (1989). *Genetic algorithms in search, optimization and machine learning*. Addison Wesley: Reading, MA.

Goodman, J.M., Lamson, A.L., Williams, R., Hylock, R.H., Jensen, J., Delbridge, T. (2018). Operationalizing frequent use: Research constructed on groundless definitions. Poster presented at *Collaborative Family Healthcare Association* conference. Rochester, NY.

Guyon, I., Gunn, S., Nikravesh, M. and Zadeh, L. (2006). *Feature extraction: Foundations and applications*. Springer.

Han, J. & Kamber, M. (2006). *Data mining: Concepts and techniques*. San Francisco: Elsevier.

Hansagi, H., Olsson, M., Sjöberg, S., Tomson, Y., & Göransson, S. (2001). Frequent use of the hospital emergency department is indicative of high use of other health care services. *Annals of Emergency Medicine, 37*, 561-567. doi: 10.1067/mem.2001.111762

Healthcare Cost and Utilization Project. (2015). 2015 Healthcare Cost and Utilization Project (HCUP) databases: Change in structure and data elements caused by transition to ICD-10-CM/PCS. Retrieved on January 4, 2018a from: https://www.hcup-us.ahrq.gov/datainnovations/2015HCUPStateDatabases04072017.pdf

Healthcare Cost and Utilization Project. *HCUP coding practices.* Retrieved January 4, 2018b from: https://www.hcup-us.ahrq.gov/db/coding.pdf

Healthcare Cost and Utilization Project. *Overview of HCUP*. Retrieved January 4, 2018c from: https://www.hcup-us.ahrq.gov/overview.jsp

Healthcare Cost and Utilization Project. *Overview of the State emergency department databases*. Retrieved January 4, 2018d from: https://www.hcup-us.ahrq.gov/seddoverview.jsp

Healthcare Cost and Utilization Project. *Overview of the State inpatient databases.* Retrieved January 4, 2018e from: https://www.hcup-us.ahrq.gov/sidoverview.jsp#data

Healthcare Cost and Utilization Project. (2017). *User guide: HCUP supplemental variables for revisit analyses*. Retrieved on January 31, 2018 from https://www.hcup-us.ahrq.gov/toolssoftware/revisit/UserGuide_SuppRevisitFilesCD.pdf

Holland, J. (1975). *Adaptation in natural and artificial systems*. University of Michigan Press: Ann Arbor.

Hunt, K. A., Weber, E. J., Showstack, J. A., Colby, D. C., & Callaham, M. L. (2006). Characteristics of frequent users of emergency departments. *Annals of Emergency Medicine, 48*, 1-8. doi: 10.1016/j.annemergmed.2005.12.030

Locker, T. E., Baston, S., Mason, S. M., & Nicholl, J. (2007). Defining frequent use of an urban emergency department. *Emergency Medicine Journal, 24*, 398-401. doi:10.1136/emj.2006.043844

Mitchell, M. (1998). *An introduction to genetic algorithms* (3rd ed). Bradford.

Pereira, M., Singh, V., Hon, C., McKelvey, T., Sushmita, S., & De Cock, M. (2016). Predicting future frequent users of emergency departments in California State. Paper presented at the *International Conference on bioinformatics, computational biology, and health informatics*. doi:10.1145/2975167.2985845

RapidMiner. (n.d.-e). *RapidMiner*. Retrieved from https://rapidminer.com/

RapidMiner. (n.d.-b). *Backward elimination.* Retrieved on March 16, 2018 from https://docs.rapidminer.com/latest/studio/operators/modeling/optimization/feature_selection/optimize_selection_backward.html

RapidMiner. (n.d.-d). *Evolutionary (optimize selection)*. Retrieved on March 16, 2018 from https://docs.rapidminer.com/latest/studio/operators/modeling/optimization/feature_selection/optimize_selection_evolutionary.html

RapidMiner. (n.d.-a). *Forward selection*. Retrieved on March 16, 2018 from https://docs.rapidminer.com/latest/studio/operators/modeling/optimization/feature_selection/optimize_selection_forward.html

RapidMiner. (n.d.-c). Optimize selection. Retrieved on March 16, 2018 from https://docs.rapidminer.com/latest/studio/operators/modeling/optimization/feature_selection/optimize_selection.html

vonBertalanffy, L. (1968). *General systems theory: Foundations, development, applications*. New York: George Braziller.

Weber, E. J. (2012). Defining frequent use: The numbers no longer count. *Annals of Emergency Medicine, 60*, 33-34. doi: 10.1016/j.annemergmed.2012.02.019

Wu, J., Grannis, S. J., Xu, H., & Finnell, J. T. (2016). A practical method for predicting frequent use of emergency department care using routinely available electronic registration data. *BMC Emergency Medicine, 16*, 12. doi:10.1186/s12873-016-0076-3

Zuckerman, S., & Shen, Y. C. (2004). Characteristics of occasional and frequent emergency department users: Do insurance coverage and access to care matter? *Medical Care, 42,* 176-182

CHAPTER 5: FREQUENT EMERGENCY DEPARTMENT USER PATIENT PHENOTYPES: DEVELOPMENT OF AN EMPIRICAL, THEORY-GROUNDED DEFINITION USING POPULATION HEALTH DATA

In 2015 there were just under 137 (136.9) million visits to the ED in the U.S., equaling 43.3 visits to the ED per one-hundred persons for that year (CDC, 2016). This is up from 90.3 million, or 34.2 visits per one-hundred persons, in 1996. In fact, the annual frequency of U.S. ED visits is increasing at a rate faster than population growth (Tang, Stein, Hsia, Maselli, & Gonzales, 2010). While the population grew by fifteen percent from 1997 to 2007, the number of annual ED visits increased by 43 percent—almost a three-fold increase (National Center for Health Statistics, 2009). As a result of the increasing number of annual ED visits, the Institute of Medicine described the state of emergency care in the U.S. as "at the breaking point" (Institute of Medicine, 2006).

In 2016, just under twenty-percent (19.4%) of U.S. adults age eighteen years or older visited the emergency department one or more times, and nearly seven percent (6.8%) visited two or more times (ED; Centers for Disease Control, 2016). Previous researchers have shown that a portion of the patients that visit the ED (~ 8%) account for many of these visits (28%), when defined as four or more visits in one year (so-called "frequent users"; Hunt, Weber, Showstack, Colby, & Callahan, 2006).

Frequent ED use has most commonly been operationalized as number of visits per year (Goodman et al., 2018). The original goal of creating such definitions was to address the issue of overcrowding in the ED, by focusing on reducing the number of visits made by a given patient (Cook et al., 2004; Hunt et al., 2006; Naughton et al., 2010; Sun, Burstin, & Brennan, 2003). This research has highlighted the fact that there is a population of individuals that visit the ED at a higher rate than the general population, and have greater healthcare needs (Byrne et al., 2003

Fuda & Immekus, 2006; Hunt, Weber, Showstack, Colby, & Callahan, 2006), and greater overall healthcare usage across healthcare services (e.g. primary, specialty care, etc.; Byrne et al., 2003; Chan & Ovens, 2002; Hansagi, Olsson, Sjöberg, Tomson, & Göransson, 2001). However, the bulk of research that employs such definitions of frequent ED use lack empirical basis or theoretical foundation (Goodman et al., 2018), and to date there is no standard definition of frequent ED use (Weber, 2012).

In their systematic review, Goodman and colleagues (2018) found that many articles (45.1%) that included a definition of ED use offered no justification for the definition used in their study, and less than three percent (2.5%) provided empirical evidence for the selection of their criteria. The few articles that provided empirical evidence ultimately resorted to using arbitrary "breakpoints" based on number of ED visits to identify and group patients (e.g., Doupe et al., 2012), or utilized an arbitrary number of ED visits to group patients and then incorporated demographic and diagnostic variables to improve the performance of their models (e.g., Locker, Baston, Mason, & Nicholl, 2007). The findings below underline the need for empirical understanding of ED utilization that takes into account systemic factors associated with use.

When researchers only focus on the number of visits individuals make to the ED, this naturally informs interventions and studies focused on reducing the number of visits as the measure of success, rather than understanding more about the root cause of use, or how interventions might impact health outcomes (Goodman et al., 2018). Without a better understanding and systemic definition of frequent ED use—one that is grounded in theory and supported by empirical data—assumptions are made about utilization. The current definitions of frequent ED use and the actions taken in relation to presumed frequent ED utilization (based on number of visits alone), could be detrimental to patient care and outcomes. If this population is

indeed both heterogenous and sicker, then it is appropriate to question whether a one-size-fits-all goal, such as reducing the number of ED visits made by these individuals, is appropriate. It is also possible that by focusing on and incentivizing a reduction in the number of visits without understanding the systemic needs of patients, people will not receive the care they need, which could lead to negative health outcomes.

Importance

Weber (2012) argued, "frequent use is only 'too frequent' if the patient could have been better served in another setting or with another approach (p. 33). Furthermore, Weber concluded that instead of asking how many visits are "too many," we should be asking whether patients are getting the care they need. The present study aims to address the limitations of previous research by comparing the performance of supervised clustering algorithms that identify and group patients based on the most common definitions of frequent ED use found in the literature (i.e.,3+, 4+, 5+ visits per year; Goodman et al., 2018) to unsupervised clustering algorithms that take into account all the systemic factors associated with patients' ED use (e.g., social location, number of visits, diagnosis type) in order to identify subpopulations of ED patients that people fall into. The authors of this study aimed to determine whether number of ED visits is a useful way to categorize frequent use patients or whether taking a systemic view of ED use is a more useful way to identify ED patient subgroups.

MATERIALS AND METHODS

The purpose of this study was to (a) determine if clustering algorithms could be used to identify unique ED patient clusters or cohorts and (b) test the following specific hypotheses:

1. Clustering with feature selection (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015) produces better fitting clusters than clustering based on number of visits to the

ED. See data analysis section for a definition of best fit. Feature selection is the process in data mining used to identify the most relevant features for classification in clusters. Relevant features of a dataset are detected, and irrelevant and redundant ones are discarded with the goal of obtaining a subset of items that properly describe the issue or problem of focus while minimizing negative effects on performance of model (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015).

2. Using features selection, patients that visit the ED across multiple, consecutive years will be clustered into different cohorts than those that only visit the ED during a single year, with no use in the following year.

Study Design

A population health dataset, including all ED visits in the State of Florida for 2011-2015 was analyzed in order to (a) identify unique ED patient subgroups and (b) ascertain which variables associated with use distinguish these groups from one another. The performance of unsupervised clustering algorithms, aided by Gini (G) and Sum of Squares (SSa) tests (unsupervised) and supervised clustering algorithms, aided by Cohen's Kappa as well as recall and precision scores were compared to determine whether grouping ED patients into subgroups on all available systemic factors associated with visits results in higher between-cluster heterogeneity (unsupervised) than grouping ED patients into subgroups based on number of visits alone (supervised).

Factorial ANOVA and Chi-square tests (Field, 2007) were performed (by year) on the results of the best performing unsupervised cluster algorithm (as determined by SSa and G measures provided by RapidMiner; RapidMiner, n.d.-e) in order to determine which variables associated with ED use differentiate the patient subgroups. ANOVA results indicated whether

there was a relationship between cluster group membership and a given continuous variable. Chi-square tests indicated whether there was an association between cluster group membership and a given categorial variable.

Setting and Selection of Participants

The State Emergency Department Databases (SEDD) is a part of the Healthcare Cost and Utilization (HCUP) set of databases (Healthcare Cost and Utilization Project, 2018a) for the State of Florida, for the years 2011-2015. These databases were used to create patient clusters in this study. The databases are developed through a Federal-State-Industry partnership bringing together data collection from State data organizations, hospital associations, private data organizations, and the Federal government, and are sponsored by the Agency for Healthcare Research and Quality (AHRQ). The Florida database was selected out of several possible databases because it has the most visits per year of all participating states and includes the Visitlink variable (i.e., a unique patient identifier that preserves patient anonymity while allowing a given patient to be tracked across visits) for all data years which we hoped would allow us to track patients across years. This was important give that the majority of frequent users stop using frequently after one year without intervention (Doupe et al., 2012; Fuda & Immekus, 2006).

HCUP includes the largest collection of longitudinal, all-payer, all encounter-level hospital care data in the U.S. (2018a). These databases contain (a) clinical and resource-use information typical for a discharge abstract, with more than 100 clinical variables (e.g., diagnoses, procedures), (b) patient demographics characteristics (e.g., sex, age, race), (c) expected payment source (e.g., Medicaid, Medicare), (d) total charges. SEDD captures discharge information on all emergency department visits that do not result in a hospital admission (HCUP,

2018b). According to the U.S. Census Bureau (2018), Florida also has a diverse population, including 16.9% Black or African American (compared to 13.4% of population nationwide), 25.6% Hispanic or Latino (compared to 18.1% of population nationwide), and 54.1% White (compared to 60.1% of population nationwide), however the Asian population (2.9%) is somewhat below the nationwide population average (5.8%).

Previous studies have had limited generalizability given the lack of a standardized definition of frequent ED use and the heterogeneity of the populations studied. The current study utilized all encounters for all patients for the clustering algorithms dataset (3 million patient/8 million encounter records, on average per year), while others ran with a 1% or 10% stratified sample (Lovric, 2011). Stratified sampling attempts to preserve the underlying distributions in the data, ensuring a fair representation of each population group in our analyses (Neyman, 1934) of all emergency department visits for all patients in the state of Florida from 2011 to 2015. This encompassed rural and urban areas across the entire state, and all patients regardless of payer (public, private, and uninsured).

Data Analysis

RapidMiner was used for clustering analyses (RapidMiner, n.d.-e). RapidMiner is a data science software platform that provides an integrated environment for data preparation, machine learning, deep learning, text mining, and predictive analytics. It is used for business and commercial applications as well as for research, education, training, rapid prototyping, and application development and supports all steps of the machine learning process including data preparation, results visualization, model validation and optimization (Hofman & Klinkenberg, 2013; RapidMinder, n.d.-e). Given that the SEDD dataset includes the entire population of ED users in Florida, completing statistical analyses on data of this size would result in finding every

relationship between cluster and variable significant. As a result, random samples of the cluster results for each year of data were selected using the statistical software R; this software was selected because it can successfully manipulate data of this size (R Studio, 2019). ANOVA and Chi-square tests were conducted on the random samples by year and across years using SPSS software (IBM, 2017).

The data was linearized to support clustering and so that there was no prioritization of variables based on the order in which they appeared in the datasets. All records were collapsed by year due to the fact that the Visitlink variable is a serial value. Collapsing the records in this manner generated one record per patient with summed Multi-level Clinical Classification Software (MCCS) codes and a normalized "days to events" calculation (i.e., how many days between each ED encounter for a given patient) and allowed clustering by patient rather than encounter. MCCS codes group specific diagnoses (i.e., tuberculosis, septicemia) into categories (i.e., infectious and parasitic diseases). MCCS was used in this analysis because with the large population size in the dataset and the number of diagnoses (i.e., 516), the clustering algorithms would not have been able to compute an answer.

Efforts to collapse records by patient across all years (i.e., Visitlink; 2009-2015), failed, and as a result, patients could only be clustered by year and not by patient across the entire dataset. The Visitlink variable is billed by HCUP as allowing researchers to connect all visits by a given patient within a calendar year, however given that the naming convention with which the state of Florida codes patients had not changed over time (P. Vidal, personal communication, October 2, 2017), it was surmised that Visitlink would remain the same. However, Visitlink failed to connect patient visits across years in the analysis for this study because Visitlink numbers are reissued each at random.

Feature selection was attempted in order to increase algorithm performance while minimizing the number of variables needed for clustering. The drawback of feature selection is loss of detail. The goal of these algorithms was to construct feature (i.e., variable) sets that, while reducing the number of elements to consider, minimized the impact of removed variables (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2015). Feature selection models that were attempted included (a) forward selection (RapidMiner, n.d.-a), (b) backward elimination (RapidMiner, n.d.-b), (c) optimize selection (RapidMiner, n.d.-c) – forward selection, (d) optimize selection – backward elimination, (e) optimize selection – evolutionary (RapidMiner, n.d.-d). Unfortunately, feature selection models were unable to run due to the size and dimensionality of the data. As an alternative, naïve attribute reduction was attempted in order to select variables for clustering that were relevant to describing the issue of ED patient subgroups while minimizing the negative effects on performance of the model. This process removed (a) all attributes with sample standard deviation < 0.025, (b) all attributes where one row accounts for > 90% of the data, (c) all attributes with unique values, (d) all attributes correlated > 0.95 (absolute values, two-tailed). For further explanation of naïve attribute reduction, see Figure 1. Once a set of variables was selected using naïve attribute reduction, the unsupervised clustering algorithms were run, using these variables to distinguish which patients should be placed into which cluster. A cluster is a collection of data objects that are similar to one another and dissimilar to the objects in other clusters. In this process, data are first partitioned into groups based on data similarity, and then labels are assigned to the relatively few groups (clusters).

The present study used unsupervised clustering algorithms (i.e., rather than defining ED use based on biases of researchers, a computer software algorithm determined how patients should be grouped) based on all the demographic and medical data available. Further, by

comparing these unsupervised clusters to supervised clusters (based on number of visits only) analyses could determine whether grouping patients based on number of visits alone (i.e., supervised), or systemic characteristics (i.e., unsupervised), is best.

A number of clustering techniques were applied to selected attributes from the dataset. Clustering algorithms that were applied to the data include (a) *K*-means (k-3 through k-7), (b) *K*-medoids, (c) Density-based Spatial Clustering of Applications with Noise (DBSCAN), (d) Expectation Maximization (EM), (e) Support Vector (SV), (f) Agglomerative (AG), (g) Top Down (k-3 through k-7) (TD), (f) *X*-means (RapidMiner, n.d.-e). Each algorithm uses a different algorithmic process to determine the best solution. The algorithms mentioned above were used to create both supervised and unsupervised clusters. The supervised versions of these clustering algorithms were instructed to group the patients by number of visits, using the most common definitions of frequent ED use found in the literature. A confusion matrix, using precision and recall scores was calculated for the top performing supervised algorithm. Cohen's Kappa was used to determine how accurately each supervised clustering algorithm was able to label patients based on number of ED visits. The unsupervised versions of the aforementioned clustering algorithms were provided with no instructions on how to group patients, leaving them to determine a solution with the goal of attaining the best performance. SSa and G were calculated to determine the performance of each unsupervised clustering algorithm. These tests indicate the level of heterogeneity between clusters. For both SSa and G, the higher the score, the more heterogenous the clusters are from one another.

R Studio (R Studio, 2019) was used to create a random sample of each model, by year (n = 200), and these random samples were also combined by model across years, as well as by year for all models. ANOVA and Chi-square tests were performed in SPSS (IBM, 2017) on the

results of the best performing unsupervised cluster algorithm (as determined by SSa and G calculations) in order to determine which variables associated with ED use differentiate the patient subgroups. Levene's tested homogeneity of variance determined that assumptions of variance were not violated, and thus One-way ANOVA and Tukey's post hoc tests were used to test whether there was a difference between clusters on all continuous variables (e.g., mean count of a diagnostic category).

RESULTS

Feature selection (i.e., naïve attribute) returned fifty-nine variables relevant to obtaining clusters. These variables included demographics (e.g., race, gender, homelessness), number of ED visits, payor type (e.g., Medicare, Medicaid, etc.), length of time between ED visits (e.g., 10 days, 200 days), specific diagnostic (e.g., mental illness, respiratory diseases), and procedure category (e.g., operations on the cardiovascular system, obstetrical procedures) codes. A complete list of these can be found in Appendix 1.

None of the supervised clustering algorithms emerged as the top performer across the years based on Cohen's Kappa. As a result, a mean Cohen's Kappa was taken for each of the algorithms, and the one with the highest mean Kappa scores (e.g., the Kappa scores for a given algorithm were added up across all five years and divided by five) was labeled the best performing supervised clustering algorithm. The algorithm with this designation was K-Means k-6. These results can be found in Table 1. Performance based on precision and recall scores for clustering using specified visit cut points (i.e., 1-2, 3+, 4+, 5+, 6+ ED visits per year), identified label 0 (1-2 ED visits) as 99%+ accurate and label 4 (count 6+ ED visits) as 60%+ accurate. However, precision and recall scores for labels 1 (3+ ED visits), 2 (4+ ED visits), and 3 (5+ ED visits) were very poor, ranging from 12-40%. The large spread of predicted scores for clusters

labeled 1 through 3 indicate how difficult it was for the algorithm to discern those labels. These results demonstrate that patients cannot be distinguished based on number of ED visits, and labeling patients based on number of ED visits, as is congruent with the literature is arbitrary and ill-informed. See Table 2 for the recall and precision score results for the supervised clustering K-Means k-6.

A number of unsupervised clustering algorithms were not able to find solutions. EM did not find any clusters, regardless of algorithm run time. AG and K-medoids started clustering, but never completed clusters, instead just continuing to try to find a cluster solution. SV found only one cluster, and labeled almost all attributes as "noise," meaning it ignored most of the input; this explains why performance scores for this algorithm were very high. As a result, none of these clustering models could be analyzed. The unsupervised clustering algorithms that produced clusters include (a) K-means, (b) X-means, (c) TD, (d) DBSCAN (1% stratified sample), (e) SV (1% stratified sample). Interquartile ranges (IQR) were calculated for the performance results by year. DBSCAN and SV both fell outside the upper limits of the IQR. Upon inspection of the model results for these two algorithms, it was discovered that DBSCAN returned 160 clusters, with the majority of patients clustered into one cluster, while the remainder of the clusters contained only five to ten patients each, and SV labeled everything as noise (i.e., it was ignored). Given these factors, DBSCAN and SV were removed from further analysis. Likewise, Topdown k-5 through k-7 fell below the lower IQR all five years. As a result, these were also excluded from further analyses.

G scores for all unsupervised models across all years were "1" (i.e., perfect heterogeneity between clusters), which suggests that this measure of performance likely did not measure what it was supposed to. SSa performance scores indicated that unsupervised clustering algorithm

models, K-Means (k-3) and X-means (k-3) each returned the best performance (i.e., SSa, G) for one year, and tied for best performance the remaining three years. See Table 3 for the performance of the unsupervised clustering algorithms. Further examination of lower performing clustering models indicated that as the number of clusters increased, performance of the models decreased. Additionally, although the number of clusters increased, cluster 0, which is the largest cluster containing 75% of patients remained the same size, while the remaining 25% of patients were further subdivided into smaller and smaller clusters as the number of clusters in the model increased.

A Levene's Test for homogeneity of variance was calculated for the random samples of cluster algorithm results; this assumption was not violated. A Fisher's Exact Test revealed that there was no association between model (i.e., K-Means k-3 and X-Means x-3) and cluster (a) 2011, X^2 (2, N = 400) = 0.84, p = 0.65, (b) 2012, X^2 (2, N = 400) = 1.06, p = 0.61, (c) 2013, X^2 (2, N = 400) = 2.15, p = 0.35, (d) 2014, X^2 (2, N = 400) = 0.67, p = 1.00, (e) 2015, X^2 (2, N = 400) = 5.44, p = 0.07. This means that the two best performing unsupervised clustering algorithms (i.e., K-Means k-3 and X-Means x-3) did not produce different cluster sizes from one another for any of the years included in this study. Given that the two algorithms' numbers of clusters and cluster sizes did not differ, further statistical analyses will be reported for only one of these models, K-Means k-3.

Overall results across years. Variables that distinguish the patient clusters from one another consistently, across the years, include payer type (i.e., Medicare, Medicaid, private insurance, self-pay, no charge, other), select diagnostic categories (i.e., mental illness, nervous system and sense organ disorders), and ED visit count (i.e., number of visits). A number of other diagnostic categories differ between clusters for some, but not all the years of the study. With

regard to demographic variables, in 2012 and 2014 "other" race, and in 2013 "black" race are associated with cluster membership, meaning the mean count of individuals identified as part of these race categories differ by cluster in those years. See Tables 4 and 5 for a summary of the results of ANOVA and Chi-square analyses by year. Due to the size constraints of this article, and the large number of significant statistical results, only ANOVA results meeting statistical significance at the $p = 0.000$ level are reported in full detail. However, for each year, the total counts (i.e., at $p = 0.000$, $p < 0.01$, $p < 0.05$) of significant outcomes are provided.

2011. The fifty-nine variables identified by feature selection for cluster analysis were included in statistical analyses to determine which systemic variables associated with patient ED use contributed to a measurable difference between the clusters in a given year. Table 4 shows the ten variables with the strongest main effects (lowest p-values) between clusters by model and year, asterisks denote their level of significance. The ten variables with the strongest main effects for K-Means k-3 were (a) *count of ED visits*, $F(2, 197) = 79.57$, $p < 0.000$, (b) *time between ED visits*, $F(2, 197) = 1{,}534.25$, $p < 0.000$, (c) having *three or more ED visits* for the year, $F(2, 197) = 51.56$, $p < 0.000$, (d) having *four or more ED visits* for the year, $F(2, 197) = 27.00$, $p < 0.000$, (e) having *five or more ED visits* for the year, $F(2, 197) = 17.29$, $p < 0.000$, (f) *mental illness diagnoses*, $F(2, 197) = 15.36$, $p < 0.000$, (g) *nervous system and sense organs diagnoses*, $F(2, 197) = 17.82$, $p < 0.000$, (h) *digestive system diagnoses*, $F(2, 197) = 9.60$, $p < 0.000$, (i) *injury and poisoning diagnoses*, $F(2, 197) = 10.42$, $p < 0.000$, and (j) *symptoms; signs; and ill-defined conditions and factors influencing health status diagnoses*, $F(2, 197) = 15.52$, $p < 0.000$. In 2011, there were (a) ten variables, $p = 0.00$, (b) seven variables, $p < 0.01$, (c) two variables, $p < 0.05$.

Post hoc comparisons using Tukey's procedures were used to determine which pairs of the three cluster means differed. Notably, (a) *count of ED visits* was lower in cluster 0 ($M = 1.22$,

SD = 0.52) than 1 (M = 3.40, SD = 1.67) and 2 (M = 3.08, SD = 1.84), (b) clusters 0 (M = 0.27, SD = 0.68) and 1 (M = 0.25, SD = 0.55) had lower mean counts of *mental health diagnoses* than cluster 2 (M = 1.25, SD = 1.54), (c) cluster 0 (M = 0.19, SD = .0.50) had a lower mean count of diagnoses of *nervous system and sense organ diagnoses* than cluster 1 (M = 1.15, SD = 1.53). A larger representation of the Tukey results (e.g., injury and poisoning diagnoses) are found in Table 4.

Fisher's Exact Test is reported instead of Chi-Square Test for categorical variables due to the fact that 18 (75%) cells had an expected count less than five patients. For K-Means k-3 primary insurance types were not equally distributed across clusters. This means that the types and amounts of each primary payer found in a given cluster were different than those found in the other clusters. These included Medicare, X^2 (14, N = 200) = 131.703, p = 0.00, Medicaid, X^2 (14, N = 200) = 131.703, p = 0.00, private insurance, X^2 (14, N = 200) = 131.703, p = 0.00, self-pay, X^2 (14, N = 200) = 131.703, p = 0.00, no charge, X^2 (14, N = 200) = 131.703, p = 0.00, and other, X^2 (14, N = 200) = 131.703, p = 0.00. These findings are consistent across all five years, and therefore will not be reported again under subsequent years' results.

2012. The variables with the strongest main effects for K-Means k-3 in 2012 were (a) *count of ED visits*, F(2, 197) = 110.53, p < 0.000, (b) *time between ED visits*, F(2, 197) = 1,457.28, p < 0.000, (c) having *three or more ED visits* for the year, F(2, 197) = 12..61, p < 0.000, (d) having *four or more ED visits* for the year, F(2, 197) = 65.83, p < 0.000, (e) having *five or more ED visits* for the year, F(2, 197) = 44.98, p < 0.000, (f) *mental illness diagnoses* , F(2, 197) = 8.82, p < 0.000, (g) *nervous system and sense organs diagnoses*, F(2, 197) = 29.94, p < 0.000, (h) *circulatory system diagnoses*, F(2, 197) = 10.38, p < 0.000, (i) *respiratory system diagnoses*, F(2, 197) = 11.67, p < 0.000, (j) *genitourinary systems*, F(2, 197) = 10.72, p < 0.000,

(k) *musculoskeletal diagnoses*, $F(2, 197) = 11.10$, $p < 0.000$, (l) *symptoms; signs; and ill-defined conditions and factors influencing health status diagnoses*, $F(2, 197) = 18.39$, $p < 0.000$, (m) *residual codes; unclassified; all E codes*, $F(2, 197) = 15.50$, $p < 0.000$, (n) *infectious and parasitic diseases*, $F(2, 197) = 8.55$, $p < 0.000$. In 2012, there were (a) fourteen variables, $p = 0.000$, (b) three variables, $p < 0.01$, (c) six variables, $p < 0.05$.

Post hoc comparisons using Tukey's procedures were used to determine which pairs of the three cluster means differed. Notably, (a) the mean *count of ED visits* was lower in cluster 0 ($M = 1.17$, $SD = 0.43$) than 1 ($M = 2.77$, $SD = 1.11$) and lower in 1 than 2 ($M = 4.73$, $SD = 2.98$; (b) cluster 0 ($M = 0.26$, $SD = 0.58$) had a lower mean count of *mental health diagnoses* than clusters 1 ($M = 0.82$, $SD = 1.53$) and 2 ($M = 1.14$, $SD = 2.30$), (b) clusters 0 ($M = 0.027$, $SD = 0.66$) and 1 ($M = 0.59$, $SD = 0.85$) have lower mean counts of *nervous system and sense organ diagnoses* than cluster 2 *($M = 1.82$, $SD = 1.84$;* (c) cluster 0 ($M = 0.44$, $SD = 0.76$) has a lower mean count of *symptoms; signs; and ill-defined conditions and factors influencing health status diagnoses* than clusters 1 ($M = 1.32$, $SD = 1.52$) and 2 ($M = 1.82$, $SD = 2.30$). A larger representation of the Tukey results (e.g., clustering around respiratory diseases and genitourinary diseases) can be found in Table 4.

2013. The variables with the strongest main effects for K-Means k-3 in 2013 were (a) *count of ED visits*, $F(2, 198) = 97.85$, $p < 0.000$, (b) *time between ED visits*, $F(2, 198) = 1{,}410.23$, $p < 0.000$, (c) having *three or more ED visits* for the year, $F(2, 198) = 112.57$, $p < 0.000$, (d) having *four or more ED visits* for the year, $F(2, 198) = 47.44$, $p < 0.000$, (e) having *five or more ED visits* for the year, $F(2, 198) = 38.30$, $p < 0.000$, (f) *mental illness diagnoses*, $F(2, 198) = 9.21$, $p < 0.000$, (g) *digestive system diagnoses*, $F(2, 198) = 18.43$, $p < 0.000$, (h) *genitourinary system diagnoses*, $F(2, 198) = 27.40$, $p < 0.000$, (i) musculoskeletal diagnoses, F(2,

198) = 10.49, p < 0.000, (j) *symptoms; signs; and ill-defined conditions and factors influencing health status diagnoses*, F(2, 198) = 15.78, p < 0.000, and (k) *residual codes; unclassified; all E codes* diagnoses, F(2, 198) = 7.90, p < 0.000. In 2013 there were, (a) eleven variables, p = 0.000, (b) seven variables, p < 0.01, (c) three variables, p < 0.05.

Post hoc comparisons using Tukey's procedures were used to determine which pairs of the three cluster means differed. Notably, (a) the mean *count of ED visits* was lower in cluster 0 (M = 1.21, SD = 0.53) than 2 (M = 2.84, SD = 1.38) and 2 was lower than 1 (M = 4.59, SD = 2.81), clusters 0 (M = 0.23, SD = 0.65) and 2 (M = 0.88, SD = 1.30) had lower mean counts of *mental health diagnoses* than cluster 1 (M = 1.11, SD = 2.38), (c) cluster 0 (M = 0.32, SD = 0.67) and 2 (M = 0.64, SD = 2.22) had lower mean counts of *musculoskeletal diagnoses* than cluster 1 (M = 1.41, SD = 1.74). A larger representation of the Tukey results (e.g.., clustering around circulatory system diagnoses and mental health diagnoses) can be found in Table 4.

2014. The variables with the strongest main effects for K-Means k-3 in 2014 were (a) *count of ED visits*, F(2, 197) = 142.47, p < 0.000, (b) *time between ED visits*, F(2, 197) = 1,487.02, p < 0.000, (c) having *three or more ED visits* for the year, F(2, 197) = 72.34, p < 0.000, (d) having *four or more ED visits* for the year, F(2, 197) = 91.69, p < 0.000, (e) having *five or more ED visits* for the year, F(2, 197) = 45.96, p < 0.000, (f) *infectious and parasitic diagnoses*, F(2, 197) = 9.39, p < 0.000, (g) *endocrine; nutritional; and metabolic diseases and immunity diagnoses*, F(2, 197) = 30.31, p < 0.000, (h) *mental illness diagnoses*, F(2, 197) = 17.56, p < 0.000, (i) diseases of the *nervous system and sense organs diagnoses*, F(2, 197) = 16.55, p < 0.000, (j) *circulatory system diagnoses*, F(2, 197) = 31.78, p < 0.000, (j) *respiratory system diagnoses* F(2, 197) = 23.85, p < 0.000, and (k) *digestive system diagnoses*, F(2, 197) = 7.95, p <

0.000, (l) *operations on the cardiovascular system*, F(2, 197) = 7.92, *p* > 0.000. In 2014 there were, (a) fifteen variables, p = 0.000, (b) two variables, p < 0.01, (c) four variables, p < 0.05.

Post hoc comparisons using Tukey's procedures was used to determine which pairs of the three cluster means differed. Notably, (a) the mean *count of ED visits* was lower in cluster 0 (M = 1.19, SD = 0.48) than 2 (M = 2.62, SD = 1.06) and lower in 2 than in 1 (M = 4.63, SD = 2.27), (b) cluster 0 (M = 0.25, SD = 0.54) had a lower mean count of *mental health diagnoses* than cluster 2 (M = 1.00, SD = 1.77), and 2 had a lower mean count than cluster 1(M = 2.00, SD = 3.42), (c) cluster 0 (M = 0.32, SD = .0.69) and 2 (M = 0.42, SD = 0.81) had lower mean counts of diagnoses of *nervous system and sense organ diagnoses* than cluster 1 (M = 2.16, SD = 3.73). A larger representation of the Tukey results (e.g., clustering around symptoms; signs; ill-defined conditions diagnoses) can be found in Table 4.

2015. The variables with the strongest main effects for K-Means k-3 in 2015 were (a) *count of ED visits*, F(2, 197) = 148.13, p < 0.000, (b) *time between ED visits*, F(2, 197) = 1,425.51, p < 0.000, (c) having *three or more ED visits* for the year, F(2, 197) = 95.36, p < 0.000, (d) having *four or more ED visits* for the year, F(2, 197) = 55.51, p < 0.000, (e) having *five or more ED visits* for the year, F(2, 197) = 60.77, p < 0.000, (f) *mental illness diagnoses*, F(2, 197) = 23.29, p < 0.000, (g) *nervous system and sense organs diagnoses*, F(2, 197) = 14.81, p < 0.000, (h) *respiratory system diagnoses*, F(2, 197) = 20.81, p < 0.000, ((i) *genitourinary diagnoses*, F(2, 197) = 12.82, p < 0.000, (j) *musculoskeletal diagnoses*, F(2, 197) = 10.95, p < 0.000, (j) *injury and poisoning*, F(2, 197) = 8.85, p < 0.000, (k) *symptoms; signs; and ill-defined conditions and factors influencing health status diagnoses*, F(2, 197) = 5.86, p < 0.000, and (l) *accidents involving playing musical instruments*, F(2, 197) = 0.42, p < 0.000. In 2015 there were, (a) thirteen variables, p = 0.000, (b) four variables, p < 0.01, (c) six variables, p < 0.05.

Post hoc comparisons using Tukey's procedures were used to determine which pairs of the three cluster means differed. Notably, (a) the mean *count of ED visits* was lower in cluster 0 (M = 1.14, SD = 0.45) than 1 (M = 1.87, SD = 1.23) and 1 had a lower mean count than 2 (M = 4.81, SD = 2.42), (b) cluster 0 (M = 0.34, SD = 0.62) had a lower mean count of *mental health diagnoses* than cluster 1 (M = 1.13, SD = 1.61), and 1 had a lower mean count than 2 (M = 2.19, SD = 2.89), (c) cluster 0 (M = 0.17, SD = .0.44) had a lower mean counts of diagnoses of *nervous system and sense organ diagnoses* than 1 (M = 0.81, SD = 1.49) and 2 (M = 1.29, SD = 2.24). A larger representation of the Tukey results (e.g., days between visits diagnoses and musculoskeletal diagnoses) can be found in Table 4.

Model stability over time. A linear regression determined that there was not a relationship between cluster and variables by year in K-Means k-3 model variables. In other words, the relationship between variables and clusters does not change over time (e.g., mean count of mental health diagnoses does not differ by year for cluster 0). A Chi-Square test was run to understand whether there was an association between cluster and year. In this analysis, the cluster variable is a categorical variable given that the numbers assigned to each cluster do not have a continuous value, but rather were used to distinguish group 0 from group 1 and 2. Year is also a categorical variable given that the ratio between two years is not meaningful, and instead year is a means of naming or differentiating the cluster results from one another for comparison. The results of the test, X^2 (8, N = 200) = 5.33, $p > 0.05$ were non-significant, suggesting that there is not an association between cluster and year. In other words, cluster size does not change across years; this suggests that there is stability in how the patients are being clustered by the algorithm over time.

Limitations

Although administrative databases such as HCUP (i.e., SEDD) provide a mechanism to look at population-based data, they are not without their limitations. Detailed patient-level clinical information such as stage of disease, tumor characteristics, or medication prescribed are not provided. Details such as findings from a test or outcome of a procedure are not recorded. Mortality can be assessed through HCUP databases, however there is no data on nonfatal and subjective patient outcomes (i.e., quality of life or patient satisfaction). While the Visitlink variable allowed clustering at the patient level, including all data for all encounters within a given year, we were not able to track patients across time with this variable, as we had hoped. This would have been valuable given that the majority of frequent ED users stop using frequently after one year without intervention (Doupe et al., 2012; Fuda & Immekus, 2006). As such, we were unable to account for how changes in use over time may impact patient clusters.

Discussion

This study contributes several noteworthy findings to the ED use literature, including (a) confirmation that using number of visits to define ED use or group patients produces arbitrary and ill-informed results, (b) grouping ED patients using data that incorporates systemic characteristics about the patients and their ED use produces stable between-year, heterogenous between-cluster results, and (c) there are specific systemic variables that distinguish the patient clusters from one another, and warrant further study. Supervised algorithms that used the most commonly cited definitions of frequent ED use (i.e., 3, 4, or 5 visits in a year; Goodman et al., 2018) were unable to distinguish which patients should be in which cluster based only on number of ED visits. This means that number of visits alone should not be used to identify or group patients.

Unsupervised models, which incorporated systemic characteristics about the patients (i.e. demographic variables such as race, gender, insurance type) and their ED use (i.e. diagnoses and procedures) formed clusters in which patients within a given cluster were alike, and patients between clusters were different (i.e. between-cluster heterogeneity). The clusters were also stable over time, meaning that the size and characteristics (e.g. mean count diagnoses within a diagnostic category) of each cluster did not change across the years included in this study. Further, the highest performing unsupervised model for which more detailed analyses were presented, K-Means k-3, had moderate to high between-cluster heterogeneity (i.e., patients between clusters were different in terms of their characteristics and the characteristics of their ED use).

When evaluating differences between clusters, across the years, variables that distinguish the patient clusters from one another consistently, included payer type (i.e., Medicare, Medicaid, etc.), select diagnostic categories (i.e., mental illness, nervous system and sense organ disorders), and ED visit count (i.e., number of visits). Perhaps surprisingly, demographics largely did not differ between clusters. Diagnostic categories that were found to have consistent between-cluster differences across years included mental illness (all years), nervous system and sense organ (4 years), and symptoms signs; and ill-defined conditions and factors influencing health status (4 years). The majority of patients (~75%) were clustered into cluster 0. This cluster consistently had a lower mean ED visit count, lower mean counts of diagnoses (i.e., fewer diagnoses), and a different primary payer profile (i.e., Medicare, Medicaid, and private insurance versus Medicaid, private insurance, self-pay, no charge, and other insurance) than the other two clusters across all years of the data. Finally, there is a cluster (it switches from cluster 1 to 2 across the years) that

has higher mean counts of ED visits and mental health diagnoses than cluster 0 across the years of this study.

The performance findings from the supervised and unsupervised models reinforce the assertion that while the mean number of ED visits by patients differ between patient clusters, this alone does not allow for identification or grouping of ED patients. Moreover, using number of ED visits alone to define ED use is an artificial construct (Goodman et al., 2018; Weber, 2012) that increases biases and assumptions instead of offering an empirical means (Goodman et al., 2018) to understand and address the needs of EDs and their patients. This empirical study underscores this argument and suggests that understanding ED use and grouping patients through the incorporation of multiple systemic levels of information about patients and their ED visits is statistically sound and meaningful.

Implications

Given that several of the patient clusters identified in this study appear to have greater health needs (i.e., clusters one and two have more diagnoses, more visits to the ED, etc. than cluster 0), it is inappropriate to continue to perpetuate the agenda of using only a number of visits or a reduction in the number of visits to the ED as an appropriate focus for research, policy, and practice. There is the potential that in doing so, the biopsychosocial, systemic health needs of patients could be ignored or marginalized. Healthcare utilization has systemic implications and using the number of ED visits as the sole means of identifying frequent ED users is an oversimplification that leads to an incomplete conclusion about patients. These conclusions marginalize the systemic factors associated with their ED use, influence research related to methods and designs that ground ED treatment protocols, and bias policy construction that should instead by influencing safe, effective, equal, and efficient care in the ED. If this

population is indeed both heterogenous and sicker, then it is appropriate to question whether a one-size-fits-all goal, such as reducing the number of ED visits made by these individuals, is appropriate. Given our findings through the unsupervised clustering analyses, the following recommendations are made:

Practice. Clinicians should take not only a patient- or family-centered stance, but also be population health-centered. Clinicians should sit at the table with administrators, financial billing specialists, and EHR technicians or informaticians in order to construct a flow chart to establish how EHR data should be drawn down on the front end (i.e., construct thoughtful EHR ED templates) to support efficient, value-based, systemic care. Furthermore, when patient cluster findings emerge, as they did in this study, providers should wonder if the factors that rose to the top occurred because of lack of evidence-based treatments for these diagnoses (making these diagnoses harder to treat) or perhaps because more specialized training is needed on specific diagnoses for those who extend care in EDs. There is no question that ED providers function in a systemic way through their evaluations of patients, perhaps findings from this study can help ED providers feel more supported by knowing that number of ED visits alone is not a differentiating factor in who they are treating but that there are systemic elements that can and should be considered as they unite as a state in what is provided to patients at large.

Research. There are a number of efforts that we recommend researchers consider with regard to ED utilization. First, researchers should investigate the specific diagnoses (e.g., mental health, nervous system) that are most common among patients within each cluster. The most common factors within each cluster should be identified, and then associations and connections can be made between these common diagnoses and outcomes such as whether they are more likely to go to the ED. Future research should discern what some of the common factors within

each of the clusters are (i.e., when looking at nervous system diagnoses, what are some of the commonalities of those who presented with this diagnosis). Findings at this level may help unveil the most common reasons that those with specific nervous system diagnoses, for example, are most inclined to go to an ED. This knowledge could then strengthen relationships between EDs and primary care through collaboration in prevention science on the most common reasons that people with specific diagnoses have bypassed a PCP to go to the ED for treatment.

Additionally, researchers, in tandem with healthcare administration should utilize reimbursement data and/or outcomes data in combination with systemic data such as that used in this study to understand value-based care from a perspective other than just a reduction in the number of ED visits. Ultimately, researchers need to help provide a more systemic analysis for the cost offset when only the number of ED visits are taken into consideration versus a systemic analysis of cost offset when ED visits are analyzed in a more systemic manner. Oftentimes by only looking at siloed data, the researcher may feel excited to see a change (e.g., a reduction in ED visits) but has not then realized that the reduction has increased mortality of patients who should have otherwise been welcomed for treatment or perhaps an increase in imprisonment rates given that is in some instances the alternative to care at the ED (i.e., mental health concerns are treated as criminal in nature rather than as symptoms or a diagnosis that can be treated).
It is also important to determine whether an unsupervised clustering model such as K-Means k-3 can be used to predict cluster group membership. This would involve applying the algorithm to patient data for which patients have already been clustered into an ED subgroup, to see if the algorithm could accurately predict the same cluster membership. The ability to predict is important as it indicates the potential for the development of successful decision support tools that could be used in the ED to identify patients and suggest useful interventions.

Finally, researchers should be collaborating with clinicians, informaticians and EHR technicians, as well as administrators to ensure that the informatics gained from the EHR are considered on the front end of EHR template creation. Oftentimes, EHRs are a collection of qualitative patient centered content rather than being seen as a potential solution to answering population health concerns that can then maximize patient centered care. Having researchers at the table with a panel of informatics experts, billing specialists, providers, and patients can help to ensure the team creates an EHR design that gathers systemic data from patient charts to further best practices in patient care as well as policy efforts based out of empirical findings.

Policy. There are at least two policy implications that were punctuated through the findings of this study. Policy efforts should focus on funding research to further understand ED patient groups from a systemic perspective. Additional funding is needed to support the development of decision support tools and interventions designed to identify and target ED patients with interventions that meet their biopsychosocial needs. Value, as it pertains to value-based care reimbursement, should be clarified to pertain to health outcomes and utilization of evidence-informed practices, not simply reducing the number of ED visits that patients make. Finally, stakeholders should create policy briefs based on empirical findings, in order to push for the development of evidence-informed policies and funding opportunities.

REFERENCES

Bolón-Canedo, V., Sánchez-Maroño, N., & Alonso-Betanzos, A. (2015). *Feature selection for high-dimensional data*. Cham, Switzerland: Springer.

Byrne, M., Murphy, A. W., Plunkett, P. K., McGee, H. M., Murray, A., & Bury, G. (2003). Frequent attenders to an emergency department: A study of primary health care use, medical profile, and psychosocial characteristics. *Annals of Emergency Medicine, 41*, 309-318. doi:10.1067/mem.2003.68

Centers for Disease Control (CDC). (2016). *National hospital ambulatory medical care survey: 2015 emergency department summary tables*. Retrieved from https://www.cdc.gov/nchs/data/nhamcs/web_tables/2015_ed_web_tables.pdf

Chan, B. T., & Ovens, H. J. (2002). Frequent users of emergency departments. Do they also use family physicians' services?. *Canadian Family Physician, 48*(10), 1654-1660.

Cohen, M. (2011). *Stratified sampling* in Lovric, M. (Ed.) International Encyclopedia of Statistical Science. Berlin: Springer.

Cook, L. J., Knight, S., Junkins, E. P., Mann, N. C., Dean, J. M., & Olson, L. M. (2004). Repeat patients to the emergency department in a statewide database. *Academic Emergency Medicine, 11*, 256-263. doi: 10.1111/j.1553-2712.2004.tb02206.x

Doupe, M. B., Palatnick, W., Day, S., Chateau, D., Soodeen, R. A., Burchill, C., & Derksen, S. (2012). Frequent users of emergency departments: developing standard definitions and defining prominent risk factors. *Annals of Emergency Medicine, 60*, 24-32. doi: 10.1016/j.annemergmed.2011.11.036.

Field, A. (2007). Analysis of variance (ANOVA). Lovric, M. (Ed.) *Encyclopedia of measurement and statistics*. Thousand Oaks, CA: Sage

Fuda, K. K., & Immekus, R. (2006). Frequent users of Massachusetts emergency departments: A statewide analysis. *Annals of Emergency Medicine, 48*, 16-e1. doi: 10.1016/j.annemergmed.2006.03.001

Goodman, J.M., Lamson, A.L., Williams, R., Hylock, R.H., Jensen, J., Delbridge, T. (2018). Operationalizing frequent use: Research constructed on groundless definitions. Poster presented at *Collaborative Family Healthcare Association* conference. Rochester, NY.

Hansagi, H., Olsson, M., Sjöberg, S., Tomson, Y., & Göransson, S. (2001). Frequent use of the hospital emergency department is indicative of high use of other health care services. *Annals of Emergency Medicine, 37*, 561-567. doi: 10.1067/mem.2001.111762

Healthcare Cost and Utilization Project. *Overview of HCUP*. Retrieved January 4, 2018a from: https://www.hcup-us.ahrq.gov/overview.jsp

Healthcare Cost and Utilization Project. *Overview of the State emergency department databases*. Retrieved January 4, 2018b from: https://www.hcup-us.ahrq.gov/seddoverview.jsp

Hunt, K. A., Weber, E. J., Showstack, J. A., Colby, D. C., & Callaham, M. L. (2006). Characteristics of frequent users of emergency departments. *Annals of Emergency Medicine, 48*, 1-8. doi: 10.1016/j.annemergmed.2005.12.030

Hofman, M. & Klinkenberg, R. (2013). *RapidMiner: Datamining use cases and business analytics applications*. Boca Raton, FL: CRC Press.

IBM Corp. (2017). *IBM SPSS Statistics for Windows, Version 25.0*. Armonk, NY: IBM Corp.

Institute of Medicine. (2006). *Hospital based emergency care: At the breaking point*. Washington (DC): National Academies Press.

National Center for Health Statistics, Ambulatory and Hospital Care Statistics Branch. (2009). *Ambulatory health care data*. Retrieved from http:// www.cdc.gov/nchs/ahcd.htm

Naughton, C., Drennan, J., Treacy, P., Fealy, G., Kilkenny, M., Johnson, F., & Butler, M. (2010). The role of health and non-health-related factors in repeat emergency department visits in an elderly urban population. *Emergency Medicine Journal, 27*, 683-687. doi: 10.1136/emj.2009.077917

Neyman, J. (1934). On the Two Different Aspects of the Representative Method: The Method of Stratified Sampling and the Method of Purposive Selection. Journal of the Royal Statistical Society, 97, 558-625. doi:10.2307/2342192

RapidMiner. (n.d.-b). *Backward elimination.* Retrieved on March 16, 2018 from https://docs.rapidminer.com/latest/studio/operators/modeling/optimization/feature_selection/optimize_selection_backward.html

RapidMiner. (n.d.-d). *Evolutionary (optimize selection)*. Retrieved on March 16, 2018 from https://docs.rapidminer.com/latest/studio/operators/modeling/optimization/feature_selection/optimize_selection_evolutionary.html

RapidMiner. (n.d.-a). *Forward selection*. Retrieved on March 16, 2018 from https://docs.rapidminer.com/latest/studio/operators/modeling/optimization/feature_selection/optimize_selection_forward.html

RapidMiner. (n.d.-f). Item distribution performance. Retrieved on February 26, 2019 from https://docs.rapidminer.com/latest/studio/operators/validation/performance/segmentation/item_distribution_performance.html

RapidMiner. (n.d.-c). Optimize selection. Retrieved on March 16, 2018 from https://docs.rapidminer.com/latest/studio/operators/modeling/optimization/feature_selecton/optimize_selection.html

RapidMiner. (n.d.-e). *RapidMiner*. Retrieved from https://rapidminer.com/

R Studio Team (2019). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL http://www.rstudio.com/.

Tang, N., Stein, J., Hsia, R.Y., Maselli, J.H., Gonzales, R. (2010). Trends and characteristics of US emergency department visits, 1997-2007. *Journal of the American Medical Association, 304*, 664-70. doi: 10.1001/jama.2010.1112.

U.S. Census Bureau. (2018). *QuickFacts.* Retrieved from https://www.census.gov/quickfacts/fact/table/fl/PST045217

Virvou, M., Alepis, E., & Troussas, C. (2012). Centroid-based clustering for student models in computer-based multiple language tutoring. Presented at the *International Conference on Signal Processing and Multimedia Applications and Wireless Information Networks and Systems* Conference. Rome, Italy.

Weber, E.J. (2012). Defining frequent use: The numbers no longer count. *Annals of Emergency Medicine,* 60, 33-34. doi:10.1016/j.annemergmed.2012.02.019

Table 1. Supervised Clustering Algorithm Performance, Cohen's Kappa

Cluster Type	2011 Kappa	2012 Kappa	2013 Kappa	2014 Kappa	2015 Kappa	Avg Kappa/Performance
DBSCAN	0.526	0.529	0.534	0.548	0.549	0.5372
K-means K-3	0.54	0.523	0.517	0.556	0.591	0.5454
K-means K-4	0.521	0.519	0.536	0.531	0.539	0.5292
K-means K-5	0.57	0.565	0.523	0.565	0.585	**0.5616**
K-means K-6	0.519	0.559	0.562	0.57	0.553	0.5526
K-means K-7	0.548	0.554	0.554	0.551	0.535	0.5484
Support Vector	0.534	0.537	0.548	0.531	0.547	0.5394
X-means	0.525	0.562	0.543	0.574	0.553	0.5514
Topdown k-3	0.538	0.525	0.518	0.547	0.567	0.539
Topdown k-4	0.524	0.543	0.536	0.552	0.543	0.5396
Topdown k-5	0.54	0.54	0.523	0.546	0.552	0.5402
Topdown k-6	0.521	0.543	0.562	0.555	0.553	0.5468
Topdown k-7	0.514	0.53	0.55	0.572	0.562	0.5456
IQR	0.019	0.02525	0.029	0.021	0.01575	0.022
Lower Quartile	0.521	0.526	0.523	0.5465	0.544	0.5321
Upper Quartile	0.54	0.55125	0.552	0.5675	0.55975	0.5541

Cohen's Kappa = 0.01–0.20 as none to slight, 0.21–0.40 as fair, 0.41– 0.60 as moderate, 0.61–0.80 as substantial, and 0.81–1.00 as almost perfect agreement

Table 2. Recall and Precision Scores for Supervised K-Means k-6 Algorithm

Year	1-2 Visits Recall	1-2 Visits Precision	3+ Visits Recall	3+ Visits Precision	4+ Visits Recall	4+ Visits Precision	5+ Visits Recall	5+ Visits Precision	6+ Visits Recall	6+ Visits Precision
2011	99.29	93.6	23.55	40.35	26.71	36.63	16	32.88	66.81	92.44
2012	99.32	94.45	38.36	43.6	17.52	28.95	14.63	33.8	57.66	96.93
2013	99.3	93.88	30.78	44.38	33.12	40.8	8.97	35.9	69.42	95.54
2014	99.29	94.27	35.89	43.47	23.28	36.79	12.28	40.38	68.56	94.91
2015	99.37	93.36	27.89	43.62	27.87	37.16	16.85	44.29	71.13	97.15

Table 3. Unsupervised Clustering Algorithm Performance

Cluster Type	**2011 G**	**2011 SSa**	**2012 G**	**2012 SSa**	**2013 G**	**2013 SSa**	**2014 G**	**2014 SSa**	**2015 G**	**2015 SSa**
DBSCAN	0.997	0.966	0.997	0.966	0.997	0.969	0.997	0.963	0.997	0.967
K-means K-3	1	**0.65**	1	0.64	1	**0.636**	1	**0.627**	1	**0.622**
K-means K-4	1	0.62	1	0.602	1	0.614	1	0.591	1	0.587
K-means K-5	1	0.59	1	0.588	1	0.596	1	0.576	1	0.577
K-means K-6	1	0.579	1	0.587	1	0.591	1	0.575	1	0.566
K-means K-7	1	0.578	1	0.583	1	0.588	1	0.572	1	0.562
Support Vector	1	1	1	1	1	1	1	1	1	1
X-means	1	**0.65**	1	**0.638**	1	**0.636**	1	**0.627**	1	0.624
Topdown k-3	1	0.61	1	0.605	1	0.597	1	0.591	1	0.589
Topdown k-4	1	0.33	1	0.326	1	0.321	1	0.318	1	0.316
Topdown k-5	1	0.312	1	0.309	1	0.305	1	0.302	1	0.301
Topdown k-6	1	0.224	1	0.224	1	0.226	1	0.226	1	0.228
Topdown k-7	1	0.175	1	0.174	1	0.174	1	0.217	1	0.219
IQR		**0.329**		**0.3215**		**0.323**		**0.317**		**0.3145**
Lower Quartile		**0.321**		**0.3175**		**0.313**		**0.31**		**0.3085**
Upper Quartile		**0.65**		**0.639**		**0.636**		**0.627**		**0.623**

Table 4. 10 ANOVAs With the Strongest Main Effects, By Year

Variables[1]	2011		2012		2013		2014		2015	
	p-value	Interaction	p-value	Interaction	p-value	Interaction	p-value	Interaction	p-value	Interaction
# ED Visits	***	0 < 1, 2	***	0<1<2	***	0<2<1	***	0<2<1	***	0<1<2
Days Between Visits	***	0 < 2 < 1	***	0<1<2	***	0<2<1	***	0<2<1	***	0<1<2
3 or More ED Visits/ Year	***	0<1,2	***	0<1<2	***	0<2<1	***	0<2<1	***	0<1<2
4 or More ED Visits/ Year	***	0 < 1	***	0<1<2	***	0<2<1	***	0<2<1	***	0<1<2
5 or More ED Visits/Year	***		***	0,1<2	***	0<1,2	***	0<1,2	***	0<1<2
Mental Illness Dx	***	0,1<2	***	0<1,2	***	0,2<1	***	0,2<1	***	0<1<2
Nervous System and Sense Organs Dx	***	0<1	***	0,1<2			***		***	0<1,2
Symptoms; Signs; Ill-defined Conditions Dx	***	0<1	***	0<1,2	***	0<1,2	***	0<12,	***	0<1,2
Digestive System Dx	***				***	0<2<1	***	0<2<1		0,2<1
Injury and Poisoning Dx	***	0<2				0<2<1			***	0<1,2
Respiratory System Dx			***	0<1,2					***	0<1<2
Musculoskeletal System Dx			***	0<2	***	0,2<1	***	2<1	***	0<1,2
Residual, Unclassified, E codes Dx			***	0<1,2	***	0<2	***	0<2		
Circulatory System Dx			***	0<1,2						
Genitourinary System Dx			***	0<1,2	***	0<1,2	***	0<1,2	***	0<1<2
Infectious & Parasitic Dx			***	0,1<2						
Endocrine Metabolic Dx										
Accidents Involving a Musical Instrument									***	0<1,2

[1]Mean count of a given variable by cluster
Dx = Diagnoses
*Significant at p < .05
**Significant at p < .01
***Significant at p < .00

Figure 1. Naïve Attribute Reduction Decision Process

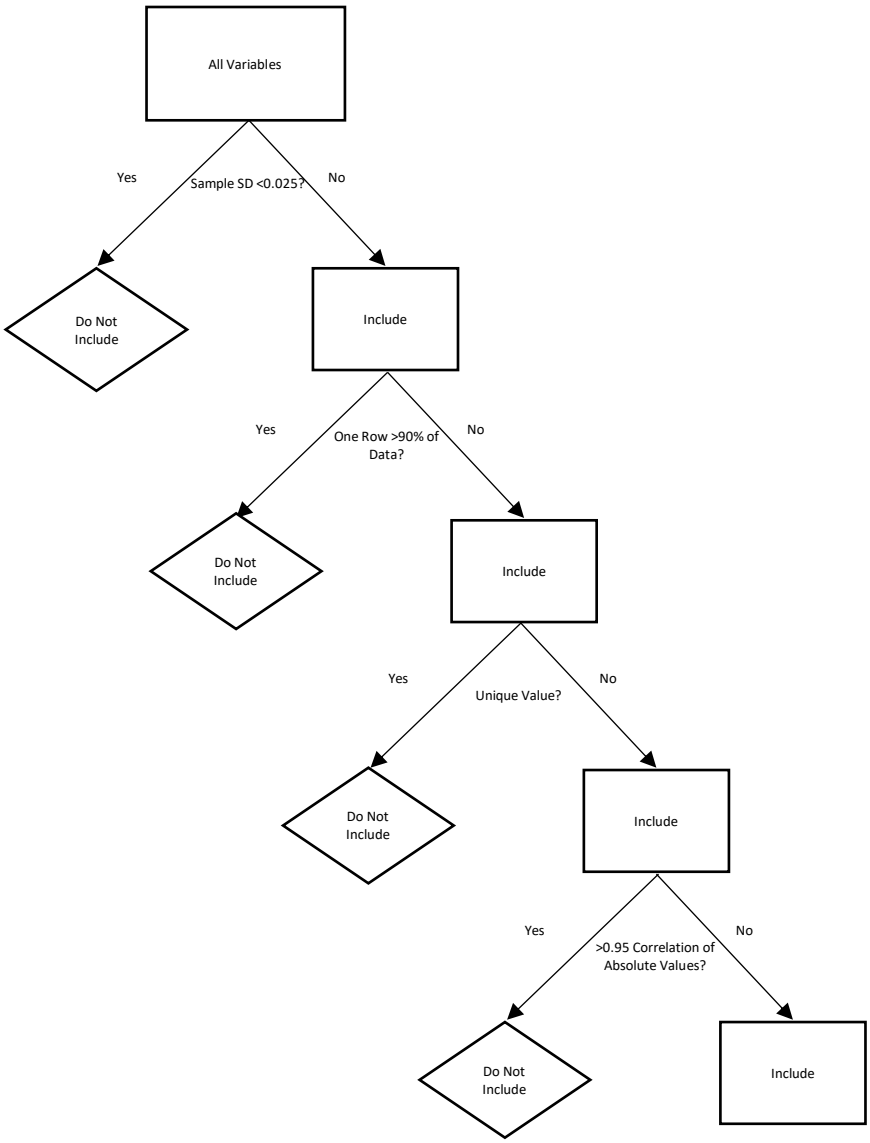
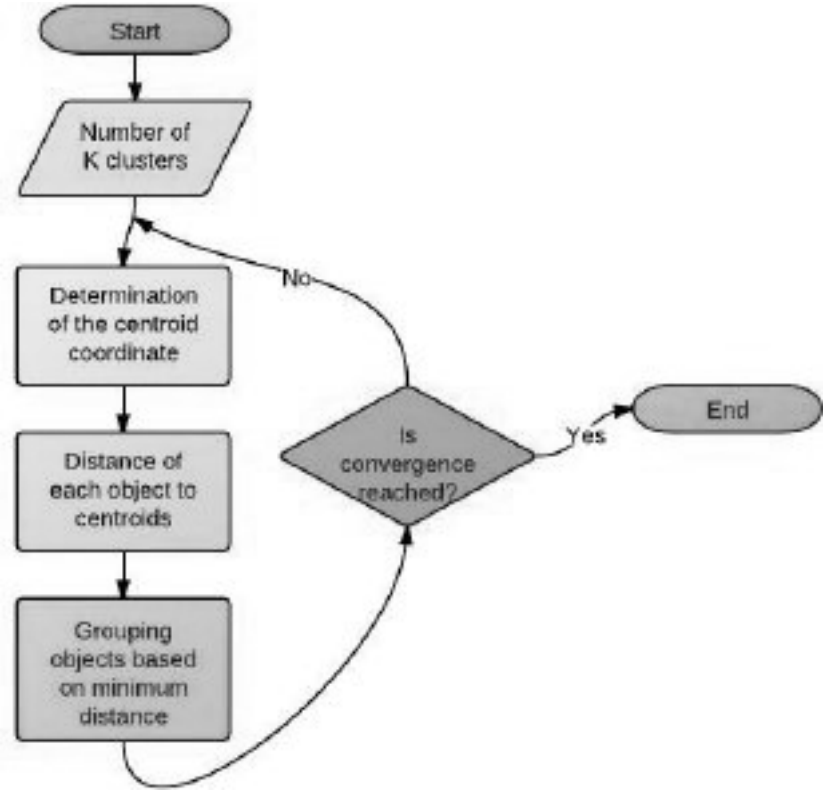


Figure 2. Example of an Unsupervised Cluster Algorithm Process* (K-Means)



*Source: Virvou, Alepis, & Troussas, 2012

CHAPTER 6: EMPIRICALLY-VALIDATED CLUSTERS OF EMERGENCY DEPARTMENT USERS: FROM DECISION GATE TO POLICY

The annual frequency of U.S. ED visits is increasing at a rate faster than population growth (Tang, Stein, Hsia, Maselli, & Gonzales, 2010). While the population grew by fifteen percent from 1997 to 2007, the number of annual ED visits increased by 43 percent—almost a three-fold increase (National Center for Health Statistics, 2009). As a result of the increasing number of annual ED visits, the Institute of Medicine (IOM) described the state of emergency care in the U.S. as "at the breaking point" (IOM, 2006). Over the past several decades researchers have focused on trying to reduce the number of visits that patients make in order to reduce overcrowding and cost (Cook et al., 2004; Hunt et al., 2006; Naughton et al., 2010; Sun, Burstin, & Brennan, 2003). These efforts have typically been targeted at so-called "frequent users." Frequent ED use has most commonly been operationalized as number of visits per year (Goodman et al., 2018b). A subset of researchers have highlighted the fact that there is a population of individuals that visit the ED at a higher rate than the general population, and have greater healthcare needs (Byrne et al., 2003; Fuda & Immekus, 2006; Hunt, Weber, Showstack, Colby, & Callahan, 2006), and greater overall healthcare usage across healthcare services (e.g. primary, specialty care, etc.; Byrne et al., 2003; Chan & Ovens, 2002; Hansagi, Olsson, Sjöberg, Tomson, & Göransson, 2001)). However, the way in which past researchers have defined and operationalized frequent ED use is linear, reductionist, and lacks both empirical basis and a theoretical foundation (Goodman et al., 2018b). As such, no standard definition of frequent ED use exists (Weber, 2012).

Using this linear and unempirical lens to conduct research, leads to interventions, policy, and information in the media that perpetuates an erroneous understanding of patient ED use. Alternatively, by identifying ED patient subgroups based on systemic patient characteristics (i.e.,

all available information about patients and their ED use), researchers could examine whether patients in each of these distinct subgroups are receiving the types of care they need. Furthermore, providers could discern what systemic factors are most influential to patient clusters in their ED system. Treatments and interventions could then be informed by these findings and tailored to the systemic, relational, and familial needs of each patient (e.g., patients with heart disease are more likely to attend the ED following a holiday on which their diets have been impacted due to dietary changes, clinicians can provide brief, culturally- and relationally-informed health behavior interventions to support patients and their families in adjusting their holiday diets to reduce the chances of a similar ED visit in the future). Policies could thereby address ED use by allocating funding for research and practice tailored to the unique ED patient subgroups and punctuate the use of protocols that employ best practices grounded in intervention research. Finally, media portrayals of ED use could cite innovative and empirically informed healthcare research/statistics rather than focusing on myths that perpetuate negative biases for those who rely on the ED for care.

This dissertation has focused on ways to discern the theoretical and empirical findings associated with frequent ED use. The first chapter of this dissertation provided context and offered background on the field of emergency medicine from inception to present day. Chapter one also introduced the problem as it relates to ED crowding and rising costs, proposed systems theory to ground the dissertation, and provided an overview of the purpose and design for a systematic review and original research.

Chapter two was a literature review that described how linear based perspectives on ED utilization limit the potential understanding of a growing healthcare concern from research, interventional, popular media and policy perspectives. This chapter raised the idea that the way

in which frequent ED use is defined informs the research done to understand both this phenomenon, its outcomes, and the types of interventions and policies that are created to address it. This assertion was used as the basis for suggesting that a new approach to defining ED use, grounded in a theory such as general systems theory, could be useful.

Chapter three, a systematic review, set out to evaluate the existing definitions of frequent ED utilization and identify the evidence used to support the existing definitions. The findings of chapter three illustrate that there was currently no empirically- or theoretically-grounded definition of ED utilization in the literature, with most (97%) articles using only one unit to operationalize frequent ED use (i.e., number of visits to the ED), and nearly half (45.1%) providing no justification for the definition used in their study. The findings of the systematic review underlined the need for an empirical understanding of ED utilization that takes into account systemic factors associated with use.

Given the need for a systemic, empirically- and theoretically- grounded definition of ED use, chapter four detailed a methodology by which to group ED patients using so-called "unsupervised" clustering algorithms based on all of their systemic characteristics (i.e., demographics, diagnoses, etc.) and a population health dataset including all ED visits for the state of Florida. The methodology also outlined means by which to compare the unsupervised approach to a supervised approach, in which clustering algorithms were instructed to group patients based on number of ED visits only. Finally, statistical methods to compare the performance of unsupervised, systemic clustering of patients to supervised clustering of patients based on number of ED visits alone were defined.

In chapter five, findings of the empirical research based on the aforementioned methodology were presented. The results of this study confirmed that using number of visits to

define ED use or group patients produces arbitrary and ill-informed results. This chapter illustrated that grouping ED patients using data that incorporates systemic characteristics about the patients and their ED use produces stable between-year, heterogenous between-cluster results.

Finally, chapter six offers a policy brief that is intended to provide stakeholders with a clear understanding of the problem as it relates to definitions of frequent use. This brief provides an alternative approach to understanding subpopulations that use the ED. Next steps in terms of research, policy, and practice targeted at addressing the research-informed needs of ED patients are recommended.

Executive Summary

Despite a lack of scientific evidence, current policy makers, researchers, practitioners, and media outlets continue to use number of ED visits as the way to operationalize frequent ED use and make sense of ED overcrowding and rising costs (Goodman et al., 2018a; Raven, 2018; Weber, 2012). Defining and addressing ED use from this unfounded and groundless construct has resulted in deterring patients from seeking necessary emergency medical attention (Rayasam & Demko, 2018; Raven, 2018), and could be leading to sicker and more costly patients, or even unnecessary and premature deaths (Raven, 2018).

Growing scientific evidence supports a shift toward looking at quality, health outcomes, and taking a systemic approach to defining and understanding ED patient subpopulations (Goodman et al., 2019; Raven, 2018). The authors of this brief have demonstrated that patients cannot be identified using number of ED visits alone, but can be grouped into subgroups that have good within-group homogeneity (i.e. patients in a given group are alike in terms of diagnoses, etc.), and between-group heterogeneity (i.e. each patient group is different from one

another in terms of diagnoses, etc.) using systemic data (i.e. all available information about each patient and their ED use; Goodman et al., 2019). Thus, the purpose of this brief is to describe the current problem as it relates to the operationalization of patient ED use, explain how the current literature defines ED use, and make recommendations for policymakers, researchers, and practitioners to take up in light of the most current empirically-based knowledge on this topic.

Background and Significance

Emergency department (ED) visit rates in the United States have outpaced population growth (Tang, Stein, Hsia, Maselli, & Gonzales, 2010), increasing from 90.3 million visits (34.2 visits per 100 persons) in 1996 to 137 million visits (43.3 visits per 100 persons) in 2015 (CDC, 2016). For two decades research, policy, and popular media portrayals have operationalized, supported, and promulgated the notion that ED visits must be reduced or avoided (Goodman et al., 2018a; Raven, 2018). Private and public payers have a long history of trying to reduce ED visits by disincentivizing patients from attending the ED through payment denials based on discharge diagnoses and a more recent history of incentivizing EDs and clinicians through annual per-patient payments (so-called "value-based payments") for reducing patient visits (Raven, 2018). Examples of this include a) the 2012 Washington State Health Care Authority attempt to pass legislation stating they would only pay for ED visits for Medicaid patients that they deemed to be medically necessary (WHSA, 2012); b) Anthem health insurance's current policy denying payments for ED visits based on a patient's discharge diagnosis (Chou, Gondi, Baker, Venkatesh, & Schuur, 2018; Rayasam & Demko, 2018); c) Wisconsin State's legislation providing up to $1,000 per patient enrolled in the state's Medical Assistance program, per year, (up to $1,500,000) to any given program that demonstrates progress in reducing emergency department visits for at least half of its enrollee population (Wisconsin, 2018).

A convincing body of evidence indicates a) most ED visits are medically necessary and most patients that seek care in the ED have urgent concerns (Hsia & Niedzwiecki, 2017); b) the necessity of an ED visit cannot often be determined in advance of the visit (Chou, Gondi, Baker, Venkatesh, & Schuur, 2018); c) so called "frequent ED users" are sicker (i.e. comorbidities, mental health diagnoses, substance use disorders, poor social determinants of health; Hunt, Weber, Showstack, Colby & Callahan, 2006; Moore, Gerdtz, Manias, Hepworth & Dent, 2007 Raven, 2018) and ED patients utilize all healthcare services (i.e. primary, secondary, tertiary) at higher rates than the general population (Hansagi et al., 2001); d) the majority of frequent use definitions lack a research basis (Goodman et al., 2018a) and there is no standard definition of frequent ED use (Weber, 2012); e) the most common definitions of frequent ED use found in the research literature, define frequent ED use as a number of visits (i.e. 3, 4, 5) over a period of time (i.e. 1 year) which is arbitrary and should not be used to identify or predict patient use (Goodman et al., 2019; Weber, 2012). These findings reinforce the assertion that instead of asking how we can reduce the number of ED visits people make, we should be asking whether they got the care they needed (Weber, 2012).

A study by Goodman and colleagues (2019) found that a particular type of algorithm (i.e. unsupervised clustering algorithm using machine learning) that decides without human input what patient (i.e. demographics) and visit data (i.e. diagnoses, procedures, etc.) can help to identify and group subpopulations of ED patients resulted in a well-performing and stable means of identifying patient subgroups across time. Goodman and colleagues found that when looking systemically (i.e. all patient demographic and ED visit medical information together), patients differ from one another across the years by primary insurance type, mean count of ED visits, and a number of diagnostic categories, including mental illness, nervous system and sense organ

disorders, and other specific diagnostic categories. These findings are important because they provide an empirically-informed alternative to the previously used definitions of frequent ED use (i.e. number of ED visits per year).

Position Statement

Based on the body of ED literature (Goodman et al., 2018b) and new empirical research findings (Goodman et al., 2019), we recommend that all future policy, research, and practice take an empirically-driven, systemic approach to defining and intervening with emergency department users, rather than using number of ED visits, which is a non-empirical and foundationless approach. The following list includes actions necessary for policymakers, researchers, and healthcare systems/practitioners to take in order to address the current crisis in Emergency Departments in the U.S. from a systemic approach:

Practice

- Advocate at the state and federal levels for value-based reimbursement that prioritizes patient needs, not number of visits
- Take a systemic approach to patient care that incorporates healthcare providers, patients, their support systems, and community partners in decision-making and interventions

Research

- Create institutional interdisciplinary teams to develop specific and systemic implementation and evaluation plans to operationalize evidence-based research focused on ED patient subgroups
- Refine our systemic, empirical understanding of ED patient subpopulations for the purposes of identifying patients in the ED according to the group they fall into, and developing targeted interventions for these groups

- Develop research informed decision-support tools to help clinicians identify and target interventions tailored to unique needs of a patient subgroup

Government Policy

- Clarify that value-based payments for emergency departments are determined by the quality in addressing patient needs, not number of ED visits made by a given patient (i.e. Wisconsin, 2018)
- Promulgate legislation that ensures private and public health insurance payers do not a) limit, b) refuse payment for, c) incentivize a reduction in emergency department visits
- Increase federal funding to develop and test a) interventions to address the unique systemic needs of ED patient subgroups, b) electronic health record (EHR) predictive and decision support tools to identify ED patient subgroup membership and recommend evidence-based interventions targeted to unique patient needs based on subgroup membership

Summary

Frequent ED use is an issue that has received considerable research, policy, and media attention over the past several decades due to concerns about the rising costs of care and overcrowding in the ED. For the sake of conducting research, developing policy, and disseminating information through popular media sources, frequent ED use has been inaccurately operationalized for years as number of ED visits over a period of time (i.e., most commonly in the literature, 3, 4, 5 or more visits in 12 months; Goodman et al., 2018b). These definitions lack the necessary theoretical and empirical foundation needed for respectable research, quality practice, and ethical policies. Goodman and colleagues (2019) found through a theoretically and empirically grounded study, that patients can be placed into subgroups that have good between-group heterogeneity (i.e. the patient groups are different from one another in terms of primary

payer types, diagnoses, etc.) and within-group homogeneity (i.e. patients in a given group are alike in terms of primary payer types, diagnoses, etc.) by using systemic data (i.e., all available information about patients and their ED use) from patients (i.e., demographic data) and their ED visit(s) (e.g., diagnoses, procedures). Given these empirical findings, this policy brief recommends that government policy, research, and practice shift from utilizing an unempirical and groundless approach to define the problem as it relates to ED utilization and identifying ED patients, to one that is empirically-grounded and systemic.

REFERENCES

Byrne, M., Murphy, A. W., Plunkett, P. K., McGee, H. M., Murray, A., & Bury, G. (2003). Frequent attenders to an emergency department: A study of primary health care use, medical profile, and psychosocial characteristics. *Annals of Emergency Medicine, 41*, 309-318. doi:10.1067/mem.2003.68

Centers for Disease Control (CDC). (2016). *National hospital ambulatory medical care survey: 2015 emergency department summary tables*. Retrieved from https://www.cdc.gov/nchs/data/nhamcs/webtables/2015edwebtables.pdf

Chan, B. T., & Ovens, H. J. (2002). Frequent users of emergency departments. Do they also use family physicians' services?. *Canadian Family Physician, 48*(10), 1654-1660.

Chou, S. C., Gondi, S., Baker, O., Venkatesh, A. K., Schuur, J. D. (2018). Analysis of a commercial insurance policy to deny coverage for emergency department visits with nonemergent diagnoses. *JAMA Network Open*. 1:e183731. doi:10.1001/jamanetworkopen.2018.3731

Cook, L. J., Knight, S., Junkins, E. P., Mann, N. C., Dean, J. M., & Olson, L. M. (2004). Repeat patients to the emergency department in a statewide database. *Academic Emergency Medicine, 11*, 256-263. doi: 10.1111/j.1553-2712.2004.tb02206.x

Fuda, K. K., & Immekus, R. (2006). Frequent users of Massachusetts emergency departments: A statewide analysis. *Annals of Emergency Medicine, 48*, 16-e1. doi: 10.1016/j.annemergmed.2006.03.001

Goodman, J.M., Hylock, R.H., Lamson, A.L., Jensen, J., Delbridge, T. (2019). Chapter 5, *Frequent emergency department user patient phenotypes: Development of an empirical,*

theory-grounded definition using population health data (Unpublished doctoral dissertation). East Carolina University, Greenville, NC.

Goodman, J. M., Lamson, A. L., Hylock, R. H., Jensen, J., Delbridge, T. (2018a). Chapter 2, The way we define frequent emergency department use informs who we define as the problem: A review (Unpublished doctoral dissertation). East Carolina University, Greenville, NC.

Goodman, J. M., Lamson, A. L., Williams, R., Hylock, R. H., Jensen, J., Delbridge, T. (2018b). Operationalizing frequent use: Research constructed on groundless definitions. Poster presented at *Collaborative Family Healthcare Association* conference. Rochester, NY.

Hansagi, H., Olsson, M., Sjöberg, S., Tomson, Y., & Göransson, S. (2001). Frequent use of the hospital emergency department is indicative of high use of other health care services. *Annals of Emergency Medicine, 37*, 561-567. doi: 10.1067/mem.2001.111762

Hsia, R. Y. & Niedzwiecki, M. (2017). Avoidable emergency department visits: A starting point. *International Journal for Quality in Health Care. 29: 642-645. doi: 10.1093/intqhc/mzx081*

Hunt, K.A., Weber, E.J., Showstack, J.A., Colby, D.C., & Callaham, M.L. (2006). Characteristics of frequent users of emergency departments. *Annals of Emergency Medicine, 48*, 1–8. doi: 10.1016/j.annemergmed.2005.12.030

Institute of Medicine. (2006). *Hospital based emergency care: At the breaking point*. Washington (DC): National Academies Press.

Moore, G., Gerdtz, M., Manias, E., Hepworth, G., & Dent, A. (2007). Socio-demographic and clinical characteristics of re-presentation to an Australian inner-city emergency department: Implications for service delivery. *BMC Public Health, 7*, 320. doi: 10.1186/1471-2458-7-320

National Center for Health Statistics, Ambulatory and Hospital Care Statistics Branch. (2009). *Ambulatory health care data*. Retrieved from http:// www.cdc.gov/nchs/ahcd.htm

Naughton, C., Drennan, J., Treacy, P., Fealy, G., Kilkenny, M., Johnson, F., & Butler, M. (2010). The role of health and non-health-related factors in repeat emergency department visits in an elderly urban population. *Emergency Medicine Journal, 27*, 683-687. doi: 10.1136/emj.2009.077917

Raven, M. C. (2018). Policies that limit emergency department visits and reimbursements undermine the emergency care system: Instead, let's optimize it. *JAMA Network Open*. *1*:e183728. doi:10.1001/jamanetworkopen.2018.3728

Rayasam, R. & Demko, P. (2018). Insurers spark blowback by reducing emergency room coverage. *Politico.* Retrieved from https://www.politico.com/story/2018/06/12/insurers-spark-blowback-by-reducing-emergency-room-coverage-612842

Sun, B. C., Burstin, H. R., & Brennan, T. A. (2003). Predictors and outcomes of frequent emergency department users. *Academic Emergency Medicine, 10*(4), 320-328.

Tang, N., Stein, J., Hsia, R. Y., Maselli, J. H., & Gonzales, R. (2010). Trends and characteristics of US emergency department visits, 1997-2007. *JAMA*, *304*(6): 664-670.

Washington State Hospital Association (WHSA). (2012). *Background information: Medicaid emergency department use*. Retrieved from http://www.wsha.org/wp-content/uploads/er-emergencies_ER-Background-Information-April-16.pdf

Weber, E. J. (2012). Defining frequent use: The numbers no longer count. *Annals of Emergency Medicine, 60*, 33-34. doi: 10.1016/j.annemergmed.2012.02.019

Wisconsin 2018 Senate Bill 742. *An act to create 49.45 (26g), 946.91 (3) (c) 3. and 946.93 (5) (c) 3. of the statutes; relating to: intensive care coordination program in the Medical Assistance program*. http://docs.legis.wisconsin.gov/2017/related/proposals/sb742.pdf. Accessed February 1, 2019.

APPENDIX A. SEARCH STRATEGY

TI "frequent use" AND TI "emergency department"
TI "frequent use" AND TI "emergency room"
TI "frequent use" AND TI "emergency care"
TI "frequent use" AND TI "emergency service"
TI "frequent users" AND TI "emergency department"
TI "frequent users" AND TI "emergency room"
TI "frequent users" AND TI "emergency care"
TI "frequent users" AND TI "emergency service"
TI "high use" AND TI "emergency department"
TI "high use" AND TI "emergency room"
TI "high use" AND TI "emergency care"
TI "high use" AND TI "emergency service"
TI "heavy use" AND TI "emergency department"
TI "heavy use" AND TI "emergency room"
TI "heavy use" AND TI "emergency care"
TI "heavy use" AND TI "emergency service"
TI "overuse" AND TI "emergency department"
TI "overuse" AND TI "emergency room"
TI "overuse" AND TI "emergency care"
TI "overuse" AND TI "emergency service"
TI "frequent utili*" AND TI "emergency department"
TI "frequent utili*" AND TI "emergency room"
TI "frequent utili*" AND TI "emergency care"
TI frequent utili*" AND TI "emergency service"
TI "high utili*" AND TI "emergency department"
TI "high utili*" AND TI "emergency room"
TI "high utili*" AND TI "emergency care"
TI "high utili*" AND TI "emergency service"
TI "heavy utili*" AND TI "emergency department"
TI "heavy utili*" AND TI "emergency room"
TI "heavy utili*" AND TI "emergency care"
TI "heavy utili*" AND TI "emergency service"
TI "over-utili*" AND TI "emergency department"
TI "over-utili*" AND TI "emergency room"
TI "over-utili*" AND TI "emergency care"
TI "over-utili*" AND TI "emergency service"
TI "overutili*" AND TI "emergency department"
TI "overutili*" AND TI "emergency room"

TI "overutili*" AND TI "emergency care"
TI "overutili*" AND TI "emergency service"
TI "frequent visitors" AND TI "emergency department"
TI "frequent visitors" AND TI "emergency room"
TI "frequent visitors" AND TI "emergency care"
TI "frequent visitors" AND TI "emergency service"
"frequent attenders" AND "emergency department"
"frequent attenders" AND "emergency room"
"frequent attenders" AND "emergency care"
"frequent attenders" AND "emergency service"
((TI frequent OR TI high OR TI heavy OR TI over AND TI use OR TI utili* OR TI users OR TI visitors OR TI attenders AND TI "emergency department" OR TI "emergency room" OR TI "emergency care" OR TI "emergency service"))

APPENDIX B. DATES AND TIMES OF INTERRATER SEARCHES

	Medline				PubMed				Scopus			
Search #	IR 1 Search Date	IR 1 Search Time	IR 2 Search Date	IR 2 Search Time	IR 1 Search Date	IR 1 Search Time	IR 2 Search Date	IR 2 Search Time	IR 1 Search Date	IR 1 Search Time	IR 2 Search Date	IR 2 Search Time
1	6/15/2017	16:31	6/21/2017	20:00	7/5/2017	12:35	7/20/2017	16:43	8/1/2017	9:08	8/3/2017	18:32
2	6/16/2017	11:16	6/21/2017	20:04	7/5/2017	12:30	7/2/2017	17:43	8/1/2017	9:15	8/3/2017	18:37
3	6/16/2017	11:17	6/21/2017	20:04	7/5/2017	14:05	7/2/2017	17:46	8/1/2017	9:22	8/3/2017	18:40
4	6/16/2017	11:18	6/21/2017	20:05	7/5/2017	14:10	7/2/2017	17:46	8/1/2017	9:23	8/3/2017	18:50
5	6/16/2017	11:20	6/21/2017	20:05	7/5/2017	14:12	7/20/2017	16:48	8/1/2017	9:29	8/3/2017	18:52
6	6/16/2017	11:37	6/21/2017	20:13	7/5/2017	14:27	7/2/2017	17:54	8/1/2017	10:03	8/3/2017	19:08
7	6/16/2017	11:41	6/21/2017	20:14	7/19/2017	17:27	7/2/2017	17:57	8/1/2017	10:05	8/3/2017	19:08
8	6/16/2017	11:44	6/21/2017	20:15	7/19/2017	17:33	7/2/2017	17:58	8/1/2017	10:07	8/3/2017	19:09
9	6/16/2017	11:45	6/21/2017	20:17	7/19/2017	17:35	7/2/2017	17:59	8/1/2017	10:10	8/3/2017	19:11
10	6/16/2017	12:00	6/21/2017	20:17	7/19/2017	17:37	7/2/2017	18:00	8/1/2017	10:12	8/3/2017	19:11
11	6/16/2017	12:01	6/21/2017	20:17	7/20/2017	11:54	7/2/2017	18:00	8/1/2017	10:13	8/3/2017	19:12
12	6/16/2017	12:02	6/21/2017	20:19	7/20/2017	11:55	7/2/2017	18:02	8/1/2017	10:14	8/3/2017	19:12
13	6/16/2017	12:06	6/21/2017	20:20	7/20/2017	11:58	7/2/2017	18:02	8/1/2017	10:15	8/3/2017	19:12
14	6/16/2017	12:07	6/21/2017	20:21	7/20/2017	12:01	7/2/2017	18:06	8/1/2017	10:15	8/3/2017	19:13
15	6/16/2017	12:09	6/21/2017	20:21	7/20/2017	12:02	7/2/2017	18:06	8/1/2017	10:16	8/3/2017	19:13
16	6/16/2017	12:11	6/21/2017	20:22	7/20/2017	12:05	7/2/2017	18:07	8/1/2017	10:17	8/3/2017	19:14
17	6/16/2017	15:49	6/21/2017	20:22	7/20/2017	12:09	7/20/2017	16:27	8/1/2017	16:32	8/3/2017	19:32
18	6/16/2017	15:52	6/21/2017	20:31	7/20/2017	12:13	7/2/2017	18:09	8/1/2017	16:35	8/3/2017	19:33
19	6/16/2	15:54	6/21/2	20:31	7/20/2	12:15	7/2/20	18:10	8/1/20	16:36	8/3/20	19:34

	017		017		017		17		17		17	
20	6/16/2017	15:55	6/21/2017	20:32	7/20/2017	12:20	7/2/2017	18:10	8/1/2017	16:39	8/3/2017	19:35
21	6/16/2017	15:57	6/21/2017	20:33	7/20/2017	13:02	7/15/2017	9:43	8/1/2017	16:45	8/3/2017	20:33
22	6/16/2017	16:00	6/21/2017	20:36	7/20/2017	13:04	7/15/2017	9:44	8/2/2017	9:27	8/3/2017	20:35
23	6/16/2017	16:02	6/21/2017	20:36	7/20/2017	13:06	7/15/2017	9:45	8/2/2017	9:29	8/3/2017	20:36
24	6/16/2017	16:04	6/21/2017	20:36	7/20/2017	13:07	7/15/2017	9:45	8/2/2017	9:29	8/3/2017	20:56
25	6/16/2017	16:06	6/21/2017	20:37	7/20/2017	13:09	7/15/2017	9:46	8/2/2017	9:43	8/3/2017	20:57
26	6/16/2017	16:08	6/21/2017	20:38	7/20/2017	13:11	7/15/2017	9:46	8/2/2017	9:46	8/3/2017	20:58
27	6/16/2017	16:09	6/21/2017	20:38	7/20/2017	13:19	7/15/2017	9:47	8/2/2017	9:48	8/3/2017	20:59
28	6/16/2017	16:11	6/21/2017	20:39	7/20/2017	13:20	7/15/2017	9:47	8/2/2017	9:49	8/3/2017	20:59
29	6/16/2017	16:12	6/21/2017	20:39	7/20/2017	13:23	7/15/2017	9:47	8/2/2017	9:51	8/3/2017	21:00
30	6/16/2017	16:13	6/21/2017	20:40	7/20/2017	13:24	7/15/2017	9:48	8/2/2017	9:52	8/3/2017	21:01
31	6/16/2017	17:02	6/21/2017	20:40	7/21/2017	14:15	7/15/2017	9:48	8/2/2017	10:38	8/3/2017	21:01
32	6/16/2017	17:05	6/21/2017	20:41	7/21/2017	14:17	7/15/2017	9:49	8/2/2017	10:51	8/3/2017	21:02
33	6/16/2017	17:06	6/21/2017	20:41	7/21/2017	14:19	7/15/2017	9:49	8/2/2017	10:53	8/3/2017	21:03
34	6/16/2017	17:08	6/21/2017	20:43	7/21/2017	14:20	7/15/2017	9:49	8/2/2017	10:57	8/3/2017	21:03
35	6/19/2017	12:15	6/21/2017	20:43	7/21/2017	14:21	7/15/2017	9:59	8/2/2017	10:58	8/3/2017	21:04
36	6/19/2017	12:19	6/21/2017	20:44	7/21/2017	14:23	7/15/2017	10:00	8/2/2017	11:00	8/3/2017	21:04
37	6/19/2017	12:23	6/21/2017	20:44	7/21/2017	14:24	7/15/2017	10:00	8/2/2017	16:46	8/3/2017	21:06
38	6/19/2017	12:28	6/21/2017	20:44	7/21/2017	14:26	7/15/2017	10:02	8/2/2017	16:49	8/3/2017	21:06
39	6/19/2017	12:33	6/21/2017	20:45	7/21/2017	14:27	7/15/2017	10:02	8/2/2017	16:51	8/3/2017	21:07
40	6/19/2017	12:39	6/21/2017	20:45	7/21/2017	14:29	7/15/2017	10:03	8/2/2017	16:53	8/3/2017	21:07

41	6/19/2017	12:41	6/21/2017	20:46	7/21/2017	14:30	7/20/2017	17:00	8/2/2017	16:56	8/3/2017	21:08
42	6/19/2017	12:44	6/21/2017	20:46	7/21/2017	14:32	7/20/2017	17:06	8/2/2017	16:57	8/3/2017	21:09
43	6/19/2017	12:48	6/21/2017	20:47	7/21/2017	14:35	7/15/2017	10:18	8/2/2017	16:59	8/3/2017	21:10
44	6/19/2017	12:44	6/21/2017	20:48	7/21/2017	14:36	7/20/2017	17:07	8/2/2017	17:01	8/3/2017	21:11
45	6/19/2017	12:58	6/21/2017	20:50	7/21/2017	14:38	7/20/2017	17:08	8/2/2017	17:05	8/3/2017	21:13
46	6/19/2017	13:05	6/21/2017	20:53	7/21/2017	14:43	7/15/2017	10:42	8/2/2017	17:14	8/3/2017	21:14
47	6/21/2017	11:14	6/21/2017	20:53	7/21/2017	14:44	7/20/2017	17:13	8/2/2017	17:14	8/3/2017	21:14
48	7/7/2017	9:33	6/21/2017	20:53	7/21/2017	14:46	7/20/2017	17:13	8/2/2017	17:15	8/3/2017	21:15
49	6/21/2017	11:40	7/2/2017	15:20	7/22/2017	12:49	7/15/2017	10:56	8/3/2017	10:01	8/3/2017	21:30

IR = Interrater

APPENDIX C: SEARCH/YIELD TABLE

	IR1 Search Results	IR2 Search Results	IR1 Unique Titles	IR2 Unique Titles	IR1 Full Text	1R2 Full Text
Medline by Ovid	3,635	3,679	180	181	99	99
PubMed	3,007	3,070	17	18	13	10
Scopus	286	326	56	57	24	27

APPENDIX D: IRB APPROVAL

EAST CAROLINA UNIVERSITY
University & Medical Center Institutional Review Board
4N-64 Brody Medical Sciences Building· Mail Stop 682
600 Moye Boulevard · Greenville, NC 27834
Office **252-744-2914** · Fax **252-744-2284** ·
www.ecu.edu/ORIC/irb

Notification of Initial Approval: Expedited

From: Biomedical IRB
To: Jessica Goodman
CC: Angela Lamson
Ray Hylock
Date: 6/26/2018
Re: UMCIRB 18-000119
Frequent Emergency Department (ED) Patient Clusters

I am pleased to inform you that your Expedited Application was approved. Approval of the study and any consent form(s) is for the period of 6/26/2018 to 6/25/2019. The research study is eligible for review under expedited category #5. The Chairperson (or designee) deemed this study no more than minimal risk.

Changes to this approved research may not be initiated without UMCIRB review except when necessary to eliminate an apparent immediate hazard to the participant. All unanticipated problems involving risks to participants and others must be promptly reported to the UMCIRB. The investigator must submit a continuing review/closure application to the UMCIRB prior to the date of study expiration. The Investigator must adhere to all reporting requirements for this study.

Approved consent documents with the IRB approval date stamped on the document should be used to consent participants (consent documents with the IRB approval date stamp are found under the Documents tab in the study workspace).

The approval includes the following items:

Name	Description
Application-for-Waiver-Form_IRB_01192018 (2).pdf	HIPAA Authorization
DUA	Dataset Use Approval/Permission
Study Methodology	Additional Items

The Chairperson (or designee) does not have a potential for conflict of interest on this study.

APPENDIX E: HCUP DATABASE ORDER APPROVAL

Your order #18870: Application Approved

Do-Not-Reply-HCUPDistributor@s-3.com Tue, Jun 19, 2018, 12:51 PM

to me

The current status of your HCUP database order is: Approved

Approved means that the HCUP Central Distributor has received your payment and any other required documentation to complete your order, and AHRQ has approved your Statement of Intended Use for the State databases you have requested.

You will receive an email when your State databases and State-related Supplemental files ship, usually within 5-7 days following this approval status update. If your order includes Nationwide databases and related Supplemental files, they will be activated for download when the physical media ship, and download instructions will be included in that email.

You may check on the status of your order at any time under Order History in My Account.

This email is automatically generated from an unmonitored email address; please do not reply. If you have questions about your order, please contact the HCUP Central Distributor at HCUPDistributor@ahrq.gov or (866) 556-HCUP (toll-free).

H·CUP AHRQ Agency for Healthcare Research and Quality Advancing Excellence in Health Care • www.ahrq.gov

INVOICE – HCUP Database Order

Order Number:	18870	**Order date:**	6/5/2018 4:55:12 PM

Supplier

HCUP Central Distributor
Social & Scientific Systems, Inc.
8757 Georgia Avenue, 12th Floor
Silver Spring, MD 20910
Telephone: (866) 556-4287 (toll-free)
Fax: (866) 792-5313 (toll-free)
Email: HCUPDistributor@ahrq.gov

TAX ID# 52-1114970

Customer Billing Address
Debra A. McLaughlin
East Carolina University
600 MOye Blvd.
Greenville, NC 27834
USA

Customer Shipping Address
Jessica Goodman
East Carolina University
241Rivers West
East Carolina University
Greenville, NC 27858
USA

Student: Yes

Tax Exemption #: 56-6000403
Organization Name: East Carolina University
Organization Type: University/college/teaching institution
Ownership of Organization: Non-profit/Government

APPENDIX F: VARIABLES SELECTED BY FEATURE SELECTION FOR CLUSTERING

Variable	Meaning of Variable
race = 1	White
race = 2	Black
race = 3	Hispanic
race = 4	Asian or Pacific Islander
race = 5	Native American
race = 6	Other Race
cnt_three_plus	3+ ED visits
cnt_four_plus	4+ ED visits
cnt_five_plus	5+ ED visits
died	Died during visit
female	Female yes or no
hispanic_x	Hispanic yes or no
homeless	Homeless yes or no
pay1_1	Medicare
pay1_2	Medicaid
pay1_3	Private Insurance
pay1_4	Self-pay
pay1_5	No Charge
pay1_6	Other Insurance
cnt	# of ED Visits/Yr
days_range	Days between visits
avg_age	Average age
avg_los	Average length of stay
dxmccs_1	Infectious and parasitic diseases
dxmccs_2	Neoplasms
dxmccs_3	Endocrine; nutritional; and metabolic diseases and immunity disorders
dxmccs_4	Diseases of the blood and blood-forming organs
dxmccs_5	Mental illness
dxmccs_6	Diseases of the nervous system and sense organs
dxmccs_7	Diseases of the circulatory system
dxmccs_8	Diseases of the respiratory system
dxmccs_9	Diseases of the digestive system
dxmccs_10	Diseases of the genitourinary system
dxmccs_11	Complications of pregnancy; childbirth; and the puerperium
dxmccs_12	Diseases of the skin and subcutaneous system
dxmccs_13	Diseases of the musculoskeletal system
dxmccs_14	Congenital anomalies
dxmccs_15	Certain conditions originating in the perinatal period
dxmccs_16	Injury and poisoning
dxmccs_17	Symptoms; signs; and ill-defined conditions and factors influencing health status
dxmccs_18	Residual codes; unclassified; all E codes

e_mccs_5	Activities involving dancing and other rhythmic movement
e_mccs_18	Activities involving playing musical instrument
prmccs_1	Operations on the nervous system
prmccs_2	Operations on the endocrine system
prmccs_3	Operations on the eye
prmccs_4	Operations on the ear
prmccs_5	Insertion of Catheter, Spinal Stimulator, and Injection into Spinal Canal
prmccs_6	Operations on the respiratory system
prmccs_7	Operations on the cardiovascular system
prmccs_8	Operations on the hemic and lymphatic system
prmccs_9	Operations on the digestive system
prmccs_10	Operations on the urinary system
prmccs_11	Operations on the male genital organs
prmccs_12	Operations on the female genital organs
prmccs_13	Obstetrical procedures
prmccs_14	Operations on the musculoskeletal system
prmccs_15	Operations on the integumentary system
prmccs_16	Miscellaneous diagnostic and therapeutic procedures